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ORIGINAL ARTICLE

Performance prediction, pacing profile and running pattern of elite 1-h track running events

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Abstract

Purpose This study aimed at comparing the predictive accuracy of the power law (PL), 2-parameter hyperbolic (HYP) and linear (LIN) models on elite 1-h track running performance, and evaluating pacing profile and running pattern of the men's best two 1-h track running performances of all times.

Methods The individual running speed–distance profile was obtained for nine male elite runners using the three models. Different combinations of personal bests times (3000 m-marathon) were used to predict performance. The level of absolute agreement between predicted and actual performance was evaluated using intraclass correlation coefficient (ICC), paired *t* test and Bland–Altman analysis. A video analysis was performed to assess pacing profile and running pattern.

Results Regardless of the predictors used, no significant differences ($p > 0.05$) between predicted and actual performances were observed for the PL model. A good agreement was found for the HYP and LIN models only when the half-marathon was the longest event predictor used (ICC = 0.718–0.737, $p < 0.05$). Critical speed (CS) was highly dependent on the predictors used. Unlike *CS*, PL_{V20} (i.e., the running speed corresponding to a 20-min performance estimated using the PL model) was associated with 1-h track running performances ($r = 0.722$–0.807, $p < 0.05$). An even pacing profile with minimal changes of step length and frequency was observed.

Conclusions The PL model may offer the more realistic 1-h track running performance prediction among the models investigated. An even pacing might be the best strategy for succeeding in such running events.

Keywords Fatigue · Power law · Intensity–duration profile · Critical speed · Step length · Step frequency

Introduction

The 1-h track running event is a unique competition among the track and field disciplines, as it is the only running race in which time, rather than distance, is fixed. Although there is a large body of literature focusing on the analysis of different endurance running events and world records [1–5], the 1-h track running event has surprisingly received very little scientific interest. Considerable scientific insights about different endurance running events have been gained from the analysis of the individual running speed–distance (or time) relationship [1–3, 6–10], classically used to evaluate endurance capacity and predict endurance running performance [1, 6–13]. However, few studies have attempted to predict 1-h track running performance [12, 14]. Moreover, while there is a large body of literature focusing on the analysis of pacing profile and running pattern during distance-based running events [15, 16], no studies have ever

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investigated them during the 1-h track running event (i.e., a time-based event). As a result, very little is known about this unique running event.

Analyzing the individual relationship between running speed and distance of elite athletes performing the 1-h track running provides an opportunity to gain new insight on this kind of events. It is well recognized that the capacity to sustain a given running speed decreases as the distance increases [3, 17, 18]. This negative exponential decay of the running speed–duration relationship was early described using the power law (PL) model:

$$s = cd^{\alpha},$$

where s is the running speed (m·s^{-1}), c and α are constants and d is the running distance covered. The PL model has also been used to characterize individual intensity–duration profiles with the purpose of predicting endurance performance [14, 19–21]. Nevertheless, very little is known about the predictive accuracy of the PL model on 1-h track running performance. Some data suggest that when using athletes' personal best times (PB), the PL model can offer a better estimation of elite long-distance running performance compared to other common models, such as the 2-parameter hyperbolic (HYP) and linear (LIN) models (i.e., the linear representation of the HYP model) [14, 22]. However, these models have traditionally been preferred to the PL model for the prediction of endurance running performance [1, 6, 7, 9–11, 13, 23], 1-h track running performance included [12]. Interestingly, although some data suggest that the PL model may better predict elite 1-h track running performance compared to the HYP model [14, 20], this hypothesis is yet to be tested.

Pacing profile, defined as the distribution of the running pace over a competition, is an important contributory factor of endurance running performance [4, 15, 24, 25]. Whereas several studies have investigated the association between pacing profile and outcomes of different elite endurance running events [4, 15, 16, 24, 26, 27], no studies have focused on the elite 1-h track running pacing profile before. The need for a different performance strategy is plausible, because attempting to run as far as possible in a given amount of time is different proposition from attempting to run a fixed distance in the shortest possible time. Thus, analyzing elite athletes' pacing profile during such events could benefit both coaches and athletes in choosing the best pacing strategy to adopt during competitions.

It is also important to note that running speed (and its changes over time—i.e., pacing) is directly determined by the product of step length and step frequency. Therefore, analyzing athletes' running pattern is essential and can provide further important information to coaches and athletes. For instance, it has been reported that elite/competitive endurance runners generally possess higher step lengths compared to recreational/amateur runners [28, 29]. A strong negative correlation has also been found between step length and time to complete a half-marathon [30], while no correlation has been observed between step frequency and endurance performance [30]. However, to the best of our knowledge, the elite 1-h track running pattern has never been investigated. Moreover, since preferred step lengths and frequencies may significantly change depending on where athletes run (e.g., treadmill vs overground) [31], it is very important to analyze running patterns during real-competitive settings. Accordingly, a running pattern analysis of the recent 1-h track running world record would represent a promising opportunity to gain new insights on such events.

Therefore, the aims of this study were to: (1) test and compare the predictive accuracy of the PL, HYP and LIN models on elite 1-h track running performance. Since the use of different models' predictors may provide different performance estimates [32–34], the predictive accuracy of these models was assessed using different PB of the events ranging between the 3000 m and the marathon; and (2) evaluate the pacing profile and running pattern of the men's best two 1-h track running performances of all times, performed at the World Athletics Wanda Diamond League Meeting 2020 in Brussels. It was hypothesized that the PL model would better predict elite 1-h track running performance compared to the HYP and LIN models.

Methods

Design and secondary data collection

This is a computational/observational study involving the analysis of secondary performance data of elite endurance runners. This study was reviewed and approved by the Ethics Committee of the University of Essex (ETH2021-0765).

Since one aim of this study was to test the predictive capacity of different models, it was necessary to identify elite runners who had competed in 1-h track running events and having also previously competed in 5000 m, 10,000 m, half-marathon and marathon events (see "Data analysis" for more details). Nine male elite runners fitting these criteria were identified and selected (aged 31 ± 4 years at the time they performed their 1-h track PB) from the 217 performances recorded in the all-time men's best 1-h runs ranking. Eight of the selected runners also competed in 3000 m events and their PB was included in the analysis (see "Data analysis"). To note, for one runner we considered the 3000 m event performed following the 1-h track PB (see Table 1), as this was the only official 3000 m event available. Data were obtained from two databases freely available online

Table 1 Athletes' personal best performances

Athlete	3000 m	5000 m	10,000 m	Half marathon	Marathon	1-h (m)
1						
Speed (m·s^{-1})	6.63	6.47	6.22	5.91	5.62	21,330
Time (seconds)	452.6	773.1	1606.6	3572.0	7511.0	
Date (year)	2016	2011	2011	2015	2018	2020
2						
Speed (m·s^{-1})	6.52	6.37	6.04	5.69	5.63	21,322
Time (seconds)	460.4	784.9	1656.4	3710.0	7489.0	
Date (year)	2015	2018	2014	2017	2020	2020
3						
Speed (m·s^{-1})	6.74	6.58	6.32	5.97	5.58	21,285
Time (seconds)	445.1	759.4	1582.8	3535.0	7556.0	
Date (year)	1998	1998	1998	2006	2006	2007
4						
Speed (m·s^{-1})	6.58	6.35	6.14	5.67	5.24	21,101
Time (seconds)	455.7	787.8	1628.2	3723.0	8049.0	
Date (year)	1989	1989	1989	1988	1986	1991
5						
Speed (m·s^{-1})		6.08	5.96	5.76	5.24	20,855
Time (seconds)		823.0	1679.2	3664.0	8059.0	
Date (year)		1987	1987	1987	1989	1990
6						
Speed (m·s^{-1})	6.35	6.25	6.08	5.88	5.59	20,703
Time (seconds)	472.6	800.2	1644.8	3588.0	7548.0	
Date (year)	2017	2017	2019	2017	2017	2020
7						
Speed (m·s^{-1})	6.27	6.20	5.97	5.58	5.37	20,399
Time (seconds)	478.2	806.8	1675.2	3783.0	7851.0	
Date (year)	1999	1994	1996	1996	1995	1996
8						
Speed (m·s^{-1})	6.48	6.28	6.12	5.72	5.39	20,102
Time (seconds)	463.0	795.7	1633.5	3686.0	7833.0	
Date (year)	1999	1998	1999	2008	2004	2009
9						
Speed (m·s^{-1})	6.20	5.98	5.82	5.65	5.37	19,985
Time (seconds)	483.8	836.6	1719.1	3735.0	7863.0	
Date (year)	2012	2013	2014	2018	2019	2020

(www.alltime-athletics.com and www.iaaf.org/statistics/index.html).

Each individual running speed–distance profile was obtained using three different models: PL, HYP, and LIN models. The best fit for each model was found by minimizing the sum of the residuals (i.e., in a last-squares sense) using the Levenberg–Marquardt non-linear curve-fitting algorithm [35, 36], available in the MATLAB curve fitting toolbox (R2016a Mathworks, Natick, MA). Adjusted R^2 (R^2_{adj}) and mean absolute percentage error (MAPE) were used as goodness of fit and model accuracy measures, respectively. The 1-h track running performance was then estimated using the three predictive models and six different predictors groups, obtaining six performance predictions per each model. The agreement between the predicted and the actual 1-h track running performances was then calculated.

Data analysis

It was assumed that each PB corresponded to the athletes' maximal performance (Table 1). Each individual running speed–distance profile for each model was obtained considering six different predictors groups separately: (1) 3000 m, 5000 m, 10,000 m, half-marathon and marathon; (2) 3000 m, 5000 m 10,000 m and half-marathon; (3) 3000 m, 5000 m and 10,000 m; (4) 5000 m, 10,000 m, half-marathon and marathon; (5) 5000 m, 10,000 m and half-marathon; (6) 10,000 m, half-marathon and marathon. It was decided to choose these predictors events as the 1-h track running performance ranges among these distances, and therefore, it was expected to optimize the prediction accuracy. Moreover, the use of predictors ranging between 3000 m and 10,000 m were expected to optimize the application of the HYP and LIN models [37].

The individual running speed–distance profile obtained using the PL model was computed by fitting running speed against running distance. Subsequently, the distance at which a running speed elicits a time to exhaustion (TTE) of 60 min was computed as $D_{PL} = \sqrt[1-\alpha]{3600c}$, where D_{PL} is the predicted running distance, c and α the coefficients of the PL model.

The individual running speed–distance profile obtained using the HYP model (i.e., $t = \mathrm{ARC_{Hyp}}/v - \mathrm{CS_{Hyp}}$, where $\mathrm{CS_{Hyp}}$ is the critical speed in $\mathrm{m \cdot s^{-1}}$, $\mathrm{ARC_{Hyp}}$ is the anaerobic running capacity in meters and t is the running time) was computed by fitting running time against running speed. The model coefficients were then used to predict the 1-h track running performance (i.e., $D_{\mathrm{Hyp}} = \mathrm{ARC_{Hyp}} + \mathrm{CS_{Hyp}} \times 3600$, where D_{Hyp} is the predicted performance).

The individual running speed–distance profile obtained using the LIN model (i.e., $D_{\mathrm{Lin}} = \mathrm{CS_{Lin}} \times t + \mathrm{ARC_{Lin}}$, where $\mathrm{CS_{Lin}}$ is the critical speed, $\mathrm{ARC_{Lin}}$ is the anaerobic running capacity for the LIN model and D_{Lin} is the predicted performance) was computed by fitting running distance against running time. Subsequently, each 1-h track running performance was estimated considering $t = 3600$.

Since the temporal proximity between the predictor events (i.e., 3000 m, 5000 m, 10,000 m, half-marathon and marathon PB) and the 1-h track running event may have potentially rendered the model less accurate for some runners, a correlation analysis between [predicted–actual 1-h track performance, Δ_{abs}] and [the time interval between when the 1-h track PB was performed and the mean time of when the predictor events were performed, Δ_{T}] was computed.

It was also decided to obtain a measure similar to the average power of a 20-min time-trial, traditionally used in cycling to obtain the so-called "Functional Power Threshold". Specifically, the equivalent speed for a 20-min running TTE using the PL model coefficients (defined here as $\mathrm{PL_{v20}}$) was computed as $\mathrm{PL_{V20}} = \mathrm{PL_{D20}}/1200$, where $\mathrm{PL_{D20}}$ corresponds to $\mathrm{PL_{D20}} = \sqrt[1-\alpha]{1200c}$. Subsequently, $\mathrm{PL_{v20}}$ was compared with $\mathrm{CS_{Hyp}}$ and $\mathrm{CS_{Lin}}$ within each predictors group.

Video analysis

Two athletes broke the previous world record in the 1-h track running at the World Athletics Wanda Diamond League Meeting (4/09/2020, Brussels). To compute pacing profile, step length and step frequency of these athletes, a video analysis of the entire race was individually conducted by two experienced researchers. The free software Kinovea (v.0.8.15, www.kinovea.org) was used for the video analysis. The video was recorded at 25 Hz. Step length was computed as the total number of running steps divided by the portions of track considered. To precisely count the total number of running steps within each portion of track considered, the first and the last running steps were divided into ten equal parts. Official lines and markers on the track were used to identify the length of each analyzed portion of track. A total of 95 track segments (average length: 232 ± 131 m, range: [80, 740 m]), included between the race starting point and 21,300 m, were considered to determine the running pace. The number of running steps were computed on 57 of them only (average length: 210 ± 96 m, range: [90, 400 m]), as it was not possible to clearly identify athletes running pattern on the remaining ones. It is also worth noting that a remarkable agreement was observed between the number of steps counted by the two researchers independently, and that the differences in magnitude were rare and not larger than 2/10 of a single running step. The step frequency was computed as the total number of steps within a given track portion divided by the time run within that track portion.

Statistical analysis

All data were first checked for normality using the Shapiro–Wilk test (W), histograms, Q–Q plots and boxplots. A one-way repeated measures ANOVA was used to investigate the effect of different predictors on models' coefficients, $\mathrm{PL_{v20}}$, and performance estimates. A two-way repeated measures ANOVA (3 × 6) was used to investigate the difference between $\mathrm{CS_{Hyp}}$, $\mathrm{CS_{Lin}}$ and $\mathrm{PL_{v20}}$ across predictors groups. In the case of a significant interaction, only preplanned follow-up comparisons were performed (i.e., comparisons between $\mathrm{CS_{Hyp}}$, $\mathrm{CS_{Lin}}$ vs $\mathrm{PL_{v20}}$ within each predictors group). The Greenhouse–Geisser adjustment was performed when the sphericity assumption was not fulfilled. Paired sample t tests with Benjamini–Hochberg's p value correction were used as follow-ups (with false-discovery rate ≤ 0.05). The level of absolute agreement between predicted and actual performance was evaluated using "One-Way Random" intraclass correlation coefficient (ICC), Bland–Altman concordance analysis, and paired t test. For the Bland–Altman concordance analysis, since an actual

Table 2 Model's coefficients, adjusted R^2 (R^2_{adj}), MAPE, and Pearson's correlations for the power law (PL), 2-parameter hyperbolic (HYP), and linear (LIN) models

n = 8	Model's coefficient 1	Model's coefficient 2	R^2_{adj}	MAPE	Correlation with actual performance		Correlation with predictors' average speed	
					Model's coefficient 1	Model's coefficient 2	Model's coefficient 1	Model's coefficient 2
Model	$\overline{X} \pm$ SD [95% CI]	$\overline{X} \pm$ SD [95% CI]	$\overline{X} \pm$ SD [95% CI]	$\overline{X} \pm$ SD [95% CI]	r (p value)	r (p value)	r (p value)	r (p value)
Predictors group 1	3000 m–5000 m–10,000 m–21097.5 m–42195 m							
$\Delta_T = 4.0 \pm 2.4$								
PL	10.835 ± 1.248	-0.063 ± 0.011	0.971 ± 0.014	0.003 ± 0.001	0.490 (0.218)	−0.363 (0.376)	0.466 (0.245)	−0.304 (0.465)
	[9.792, 11.879]	[-0.073, -0.053]	[0.960, 0.983]	[0.002, 0.005]				
HYP	1284 ± 466	5.310 ± 0.180	0.949 ± 0.023	44 ± 16	−0.045 (0.921)	0.460 (0.251)	0.179 (0.671)	0.474 (0.235)
	[931, 1636]	[5.159, 5.460]	[0.930, 0.968]	[31, 57]				
LIN	861 ± 196	5.394 ± 0.154	0.999 ± 0.000	26 ± 9	0.125 (0.768)	0.488 (0.220)	0.251 (0.548)	0.593 (0.121)
	[697, 1025]	[5.266, 5.523]	[0.999, 0.999]	[18, 34]				
Predictors group 2	3000 m–5000 m–10,000 m–21097.5 m							
$\Delta_T = 4.5 \pm 2.9$								
PL	10.458 ± 1.136	-0.059 ± 0.011	0.971 ± 0.026	0.003 ± 0.002	0.636 (0.090)	−0.503 (0.204)	0.539 (0.169)	−0.354 (0.390)
	[9.509, 11.407]	[-0.068, -0.049]	[0.949, 0.993]	[0.002, 0.005]				
HYP	677 ± 162	5.574 ± 0.154	0.952 ± 0.018	24 ± 5	0.423 (0.297)	0.345 (0.402)	0.361 (0.380)	0.619 (0.102)
	[541, 812]	[5.445, 5.702]	[0.936, 0.967]	[20, 28]				
LIN	528 ± 119	5.635 ± 0.147	0.999 ± 0.000	12 ± 4	0.430 (0.288)	0.4095 (0.315)	0.347 (0.400)	0.702 (0.052)
	[428,627]	[5.512, 5.758]	[0.999, 0.999]	[9, 16]				
Predictors group 3	3000 m–5000 m–10,000 m							
$\Delta_T = 5.2 \pm 3.7$								
PL	9.730 ± 0.844	-0.051 ± 0.009	0.987 ± 0.013	0.002 ± 0.001	0.692 (0.057)	−0.503 (0.204)	0.587 (0.126)	−0.323 (0.436)
	[9.024, 10.436]	[-0.058, -0.043]	[0.976, 0.998]	[0.001, 0.003]				
HYP	292 ± 56	5.911 ± 0.145	0.987 ± 0.010	7 ± 4	0.726 (0.042)	0.548 (0.160)	0.243 (0.563)	0.901 (0.002)
	[245, 339]	[5.790, 6.032]	[0.979, 0.996]	[4, 10]				
LIN	273 ± 48	5.928 ± 0.148	0.999 ± 0.000	3 ± 2	0.660 (0.075)	0.591 (0.123)	0.406 (0.319)	0.920 (0.001)
	[233, 313]	[5.804, 6.051]	[0.999, 0.999]	[2, 5]				

$\overline{X}$ mean value, *SD* standard deviation, *95% CI* 95% confident intervals ([lower, upper]), *MAPE* mean absolute percentage error, *r* Pearson's correlation coefficient, Δ_T time interval in years. Model's coefficient 1 corresponds to c, ARC_{Hyp} and ARC_{Lin} for the PL, HYP and LIN models, respectively. Model's coefficient 2 corresponds to α, CS_{Hyp} and CS_{Lin} for the PL, HYP and LIN models, respectively

performance can be considered a gold standard measure, we plotted Δ_{abs} against actual performances instead of (predicted + actual)/2 [38] (hereinafter referred as concordance plot). The presence of a proportional bias was identified by a significant slope of the regression line [39]. The relationship between models' coefficients and actual performance, and between PL_{v20} and actual performance were evaluated using r. The relationship between models' coefficients, PL_{v20} and the average speed of each predictors groups was investigated using r. An alpha level of 0.05 was used to indicate statistical significance. All data were expressed as means ± 1SD. Effect sizes are presented as either partial eta-squared (η^2_p) or as Cohen's d (d). The SigmaPlot software was used to conduct the Bland–Altman analysis (version 12.0, Systat Software, San Jose, CA). The IBM SPSS Statistics 23 software package was used to conduct all the other the statistical analyses (SPSS Inc, Chicago, Illinois, USA).

Results

Mean coefficients, MAPE and R^2_{adj} values of the PL, HYP and LIN models obtained using different predictors groups are reported in Tables 2 and 3. The associations between the models' coefficients and the actual 1-h track running performance, and between the models' coefficients and the average running speed within each predictors group are shown in Tables 2 and 3. No significant correlation between Δ_{abs} and Δ_T was found for all the investigated models and predictors ($0.226 \le r \le 0.484$; $0.221 \le p \le 0.559$).

Single values of the models' coefficients obtained using different predictors groups for the PL, HYP and LIN models are depicted in Fig. 1. The One-Way ANOVA reveals a significant main effect of predictors groups for CS_{Hyp} and ARC_{Hyp} ($p < 0.001$, $\eta^2_P = 0.845$ and $p < 0.05$, $\eta^2_P = 0.787$, respectively), CS_{Lin} and ARC_{Lin} ($p < 0.001$, $\eta^2_P = 0.878$ and $p < 0.001$, $\eta^2_P = 0.870$, respectively), and c and α ($p < 0.05$, $\eta^2_P = 0.471$ and $p < 0.05$, $\eta^2_P = 0.488$, respectively. A significant main effect of predictors groups was also found in the 1-h track running predictions for the three models (PL: $p < 0.05$, $\eta^2_P = 0.544$, HYP: $p < 0.001$, $\eta^2_P = 0.889$, LIN: $p < 0.001$, $\eta^2_P = 0.883$) and for PL_{v20} ($p = 0.034$, $\eta^2_P = 0.457$). Figure 1 shows the follow-up comparisons, where no differences were observed for c, α and performance predictions when using the PL model (all Benjamini–Hochberg's $p > 0.054$). No differences were also found for PL_{v20} (all Benjamini–Hochberg's $p > 0.064$).

Performance predictions obtained using the different predictors groups and models are reported in Tables 4 and 5. Regardless of the predictors group used, no significant differences were found between predicted and actual 1-h track running performance when the PL model was employed. Conversely, significant differences were observed when the HYP and LIN models were used, and a good agreement between predicted and actual performances was found only when predictors groups 2 and 5 were used (i.e., only when the half-marathon was included in the model).

The concordance plots for each investigated model and predictors group are shown in Figs. 2 and 3. No significant proportional bias was found. The bias and the upper and lower limits of agreement values of the concordance plots, and ICCs are reported in Tables 4 and 5.

CS_{Hyp} and CS_{Lin} were equal to the 97 ± 1% and 98 ± 1% of the average running speed of the longest event included in the predictors group 1 (i.e., marathon), 97 ± 1% and 98 ± 0.5% in the predictors group 2 (half-marathon), 97 ± 1% and 97 ± 0.5% in the predictors group 3 (10,000 m); 97 ± 1% and 97 ± 0.5% in the predictors group 4 (marathon), 96 ± 1% and 98 ± 1% in the predictors group 5 (half-marathon), and 96 ± 1% and 97 ± 1% in the predictors group 6 (marathon).

The average running speed corresponding to PL_{V20} was found equal to 6.15 ± 0.14 $m \cdot s^{-1}$ in the predictors group 1, 6.15 ± 0.15 $m \cdot s^{-1}$ in the predictors group 2, 6.18 ± 0.15 $m \cdot s^{-1}$ in the predictors group 3, 6.15 ± 0.15 $m \cdot s^{-1}$ in the predictors group 4, 6.15 ± 0.15 $m \cdot s^{-1}$ in the predictors group 5, 6.21 ± 0.16 $m \cdot s^{-1}$ in the predictors group 6.

The Two-Way ANOVA revealed a main effect of running speed ($p < 0.001$, $\eta^2_P = 0.996$) and predictors group ($p < 0.007$, $\eta^2_P = 0.866$). A significant interaction was also found ($p < 0.001$, $\eta^2_P = 0.839$). Follow-up comparisons revealed a significant difference between PL_{V20} and CS_{Hyp} when using predictors group 1 ($p > 0.001$, $d = 4.562$), 2 ($p > 0.001$, $d = 4.450$), 3 ($p > 0.001$, $d = 5.078$), 4 ($p > 0.001$, $d = 4.549$), 5 ($p > 0.001$, $d = 3.577$) and 6 ($p > 0.001$, $d = 3.612$); and between PL_{V20} and CS_{Lin} when using predictors group 1 ($p > 0.001$, $d = 5.005$), 2 ($p > 0.001$, $d = 4.624$), 3 ($p > 0.001$, $d = 5.575$), 4 ($p > 0.001$, $d = 4.982$), 5 ($p > 0.001$, $d = 3.617$) and 6 ($p > 0.001$, $d = 3.854$).

Positive associations between PL_{V20} and the average speed of the predictors group 1 ($r = 0.991$, $p < 0.001$), predictors group 2 ($r = 0.999$, $p < 0.001$), predictors group 3 ($r = 0.994$, $p < 0.001$), predictors group 4 ($r = 0.955$, $p < 0.001$), predictors group 5 ($r = 0.984$, $p < 0.001$), and predictors group 6 ($r = 0.719$, $p < 0.05$) were observed.

The association between PL_{V20} and the actual 1-h track running performance is shown in Fig. 4. To note, positive high correlations between PL_{v20} and the actual 1-h track running performances were observed, except when the predictors group 6 was used. Conversely, no associations between CS_{Hyp}, CS_{Lin} and actual 1-h track running performances were found (Tables 2 and 3).

A total number of 5895 and 6177 running steps were counted for the 1st and 2nd men's best 1-h track runners of all times, respectively. The average number of running steps done within the portions of track analyzed corresponded to 105 ± 48 and 111 ± 51, respectively. The mean running speed of the men's best two 1-h track running performances of all times (1st: 5.925 ± 0.089 $m \cdot s^{-1}$, coefficient of variation (CV) = 1.5%, median = 5.913 $m \cdot s^{-1}$, range = [5.774, 6.410]; 2nd: 5.923 ± 0.074 $m \cdot s^{-1}$, CV = 1.2%, median = 5.912 $m \cdot s^{-1}$, range = [5.708, 6.258], respectively) are shown in Fig. 5, panel A. Step length (1st: 2.05 ± 0.02 m, CV = 1.09%, median = 2.05 m, range = [1.98, 2.15]; 2nd: 1.84 ± 0.02 m, CV = 1.2%, median = 1.84 m, range = [1.77, 1.90]) and step frequency (1st: 2.89 ± 0.02 Hz, CV = 0.81%, median = 2.89 Hz, range = [2.84, 2.99]; 2nd: 3.22 ± 0.02 Hz, CV = 0.91%, median = 3.22 Hz, range = [3.14, 3.30]) are reported in Fig. 5, panel B and C, respectively. The relative step length (i.e., ([step length/athlete's height] × 100)) was found equal to 117.3 ± 1.3% (median = 117.2%, range = [113.3, 122.6])

Table 3 Model's coefficients, adjusted R^2 (R^2_{adj}), MAPE, and Pearson's correlations for the power law (PL), 2-parameter hyperbolic (HYP), and linear (LIN) models

n=9	Model's coefficient 1	Model's coefficient 2	R^2_{adj}	MAPE	Correlation with actual performance		Correlation with predictors' average speed	
					Model's coefficient 1	Model's coefficient 2	Model's coefficient 1	Model's coefficient 2
Model	$\overline{X}\pm$SD [95% CI]	$\overline{X}\pm$SD [95% CI]	$\overline{X}\pm$SD [95% CI]	$\overline{X}\pm$SD [95% CI]	r (p value)	r (p value)	r (p value)	r (p value)
Predictors group 4	5000 m–10,000 m–21097.5 m–42195 m							
$\Delta_T=3.7\pm2.0$								
PL	11.234 ± 1.451	−0.067 ± 0.013	0.964 ± 0.035	0.003 ± 0.001	0.445 (0.230)	−0.354 (0.349)	0.375 (0.320)	−0.228 (0.555)
	[10.119, 12.350]	[−0.077, −0.057]	[0.937, 0.991]	[0.001, 0.004]				
HYP	1479 ± 487	5.259 ± 0.199	0.963 ± 0.035	29 ± 10	−0.029 (0.942)	0.364 (0.336)	−0.035 (0.950)	0.610 (0.081)
	[1104, 1853]	[5.106, 5.413]	[0.947, 0.979]	[22, 37]				
LIN	1117 ± 267	5.329 ± 0.171	0.999 ± 0.000	3 ± 1	0.107 (0.785)	0.384 (0.307)	−0.019 (0.962)	0.698 (0.037)
	[911, 1324]	[5.198, 5.461]	[0.999, 0.999]	[2, 4]				
Predictors group 5	5000 m–10,000 m–21097.5 m							
$\Delta_T=4.3\pm2.5$								
PL	10.654 ± 1.667	−0.060 ± 0.017	0.966 ± 0.040	0.002 ± 0.001	0.515 (0.156)	−0.431 (0.247)	0.499 (0.171)	−0.397 (0.290)
	[9.373, 11.936]	[−0.073, −0.048]	[0.935, 0.996]	[0.001, 0.003]				
HYP	748 ± 214	5.554 ± 0.152	0.958 ± 0.020	13 ± 3	0.328 (0.389)	0.313 (0.412)	0.357 (0.345)	0.556 (0.120)
	[584, 912]	[5.437, 5.671]	[0.943, 0.973]	[11, 16]				
LIN	648 ± 182	5.592 ± 0.145	0.999 ± 0.000	7 ± 3	0.343 (0.367)	0.348 (0.359)	0.363(0.337)	0.614 (0.079)
	[508, 788]	[5.480, 5.704]	[0.999, 0.999]	[5, 10]				
Predictors group 6	10,000 m–21097.5 m–42195 m							
$\Delta_T=3.2\pm1.5$								
PL	12.366 ± 2.406	−0.075 ± 0.019	0.920 ± 0.099	0.148 ± 0.086	0.195 (0.616)	−0.111 (0.776)	−0.012 (0.977)	0.098 (0.801)
	[10.517, 14.215]	[−0.090, −0.060]	[0.844, 0.996]	[0.077, 0.373]				
HYP	1732 ± 626	5.226 ± 0.215	0.953 ± 0.026	14 ± 4	−0.049 (0.901)	0.347 (0.360)	−0.110 (0.778)	0.650 (0.072)
	[1250, 2213]	[5.061, 5.391]	[0.933, 0.973]	[11, 17]				
LIN	1522 ± 440	5.264 ± 0.191	0.999 ± 0.000	8 ± 4	0.023 (0.953)	0.357 (0.346)	−0.131 (0.736)	0.694 (0.038)
	[1184, 1859]	[5.117, 5.411]	[0.999, 0.999]	[4, 11]				

$\overline{X}$ mean value, *SD* standard deviation, *95% CI* 95% confident intervals ([lower, upper]), *MAPE* mean absolute percentage error, r Pearson's correlation coefficient, Δ_T time interval in years. Model's coefficient 1 corresponds to c, ARC_{Hyp} and ARC_{Lin} for the PL, HYP and LIN models, respectively. Model's coefficient 2 corresponds to α, CS_{Hyp} and CS_{Lin} for the PL, HYP and LIN models, respectively

and 109.4 ± 1.1% (median = 109.4%, range = [105.4, 113.1]) for the 1st and 2nd performance, respectively (athletes' height: 1.75 m and 1.68 m, respectively). Running speeds, step lengths and step frequencies in Fig. 5 were the only variables not normally distributed ($W > 0.954$, $p < 0.05$).

Very small but significant changes of both step frequency and step length were observed over time. Specifically, a significant increment over time was found in step length ($p < 0.001$) in both performances (1st: slope = 0.0000022, intercept = 2.03, $r = 0.659$; 2nd: slope = 0.0000020, intercept = 1.81, $r = 0.666$) (Fig. 5, panel B). A concomitant significant decrement was found in step frequency ($p < 0.001$) in both performances (1st: slope = − 0.0000050, intercept = 2.90, $r = 0.478$; 2nd: slope = -0.0000058, intercept = 3.24, $r = 0.435$) (Fig. 5, panel C).

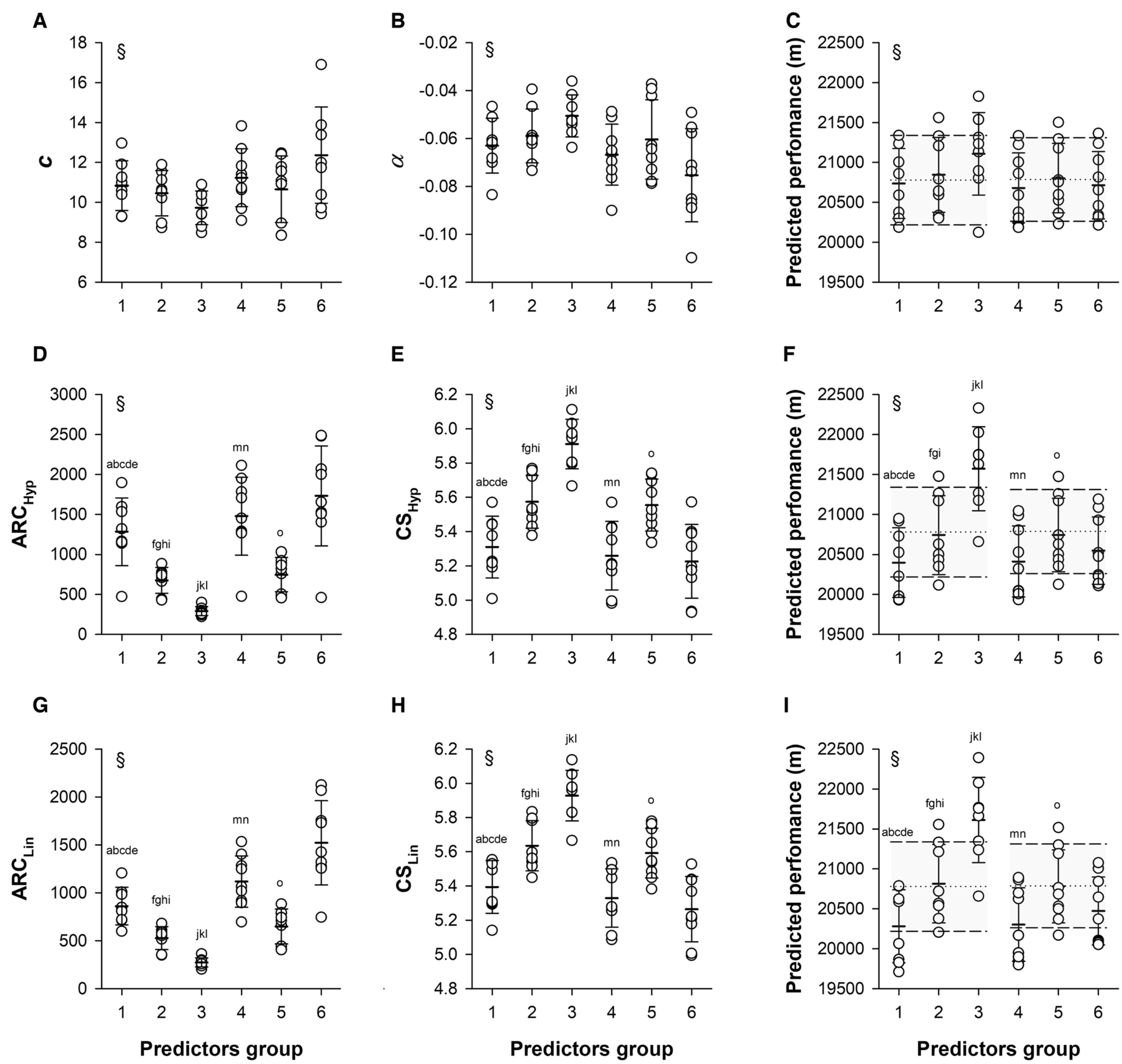

Fig. 1 Models' coefficients obtained using different predictors groups are displayed for the PL (panels **A** and **B**), HYP (panels **D** and **E**) and LIN (panels **G** and **H**) models. Panels **C**, **F** and **I** depict performance predictions using different predictors groups for the PL (panel **C**), HYP (panel **F**), and LIN (panel **I**) models, respectively. The transparent grey area shown on panels **C**, **F** and **I** represents the mean ± 1SD of the actual 1-h track running performance [dashed lines represent the mean ± 1SD, the dot line represents the mean running performance value when using predictors groups 1–3 (20,778 ± 560 m) and 4–6 (20,787 ± 525 m)]. In each panel, both individual (open circle) and mean ± SD (horizontal solid lines) values are reported for PL (top panels), HYP (middle panels) and LIN (bottom panels) models. $^{§}p < 0.05$ main effect of predictors groups. Follow-up comparisons with Benjamini–Hochberg's *p* value correction: $^{a}p < 0.05$ predictors group 1 vs predictors group 2, $^{b}p < 0.05$ predictors group 1 vs predictors group 3, $^{c}p < 0.05$ predictors group 1 vs predictors group 4, $^{d}p < 0.05$ predictors group 1 vs predictors group 5, $^{e}p < 0.05$ predictors group 1 vs predictors group 6, $^{f}p < 0.05$ predictors group 2 vs predictors group 3, $^{g}p < 0.05$ predictors group 2 vs predictors group 4, $^{h}p < 0.05$ predictors group 2 vs predictors group 5, $^{i}p < 0.05$ predictors group 2 vs predictors group 6, $^{j}p < 0.05$ predictors group 3 vs predictors group 4, $^{k}p < 0.05$ predictors group 3 vs predictors group 5, $^{l}p < 0.05$ predictors group 3 vs predictors group 6, $^{m}p < 0.05$ predictors group 4 vs predictors group 5, $^{n}p < 0.05$ predictors group 4 vs predictors group 6, and $^{o}p < 0.05$ predictors group 5 vs predictors group 6. CS_{Hyp} and CS_{Lin} estimates increase with short-event PB times (predictors group 2, 3, and 5) and decrease with longer event PB times (predictors group 1, 4, and 6)

Table 4 Actual and predicted performance, Δ_{abs}, magnitude of Δ_{abs}, ICC and concordance plot limits of agreement for the power law (PL), 2-parameter hyperbolic (HYP), and linear (LIN) models

n = 8	Actual performance	Predicted performance	Δ_{abs}	Magnitude of Δ_{abs}	$ICC_{(1,1)}$	$ICC_{(1,2)}$	Concordance plot LoA	
Model	$\overline{X}\pm SD$ (m) [95% CI]	$\overline{X}\pm SD$ (m) [95% CI]	$\overline{X}\pm SD$ (m) [95% CI]	*t*- and *p*-value (Cohen's *d*)	ICC (*p*-value) [95% CI]	ICC (*p*-value) [95% CI]	Upper (m) [95% CI]	Lower (m) [95% CI]
Predictors group 1	3000 m–5000 m–10,000 m–21097.5 m–42195 m							
PL	20,778 ± 560 [20310, 21247]	20,736 ± 438 [20307, 21102]	− 43 ± 400 [− 377, 292]	$t_{(7)} = -0.301$ $p = 0.772$ (0.107)	ICC = 0.715 (0.011) [0.141, 0.934]	ICC = 0.834 (0.011) [0.247, 0.966]	741 [142, 1340]	− 826 [− 1425, − 227]
HYP	20,778 ± 560 [20310, 21247]	20,398 ± 436 [20034, 20763]	− 380 ± 437 [− 745, − 15]	$t_{(7)} = -2.462$ = p 0.043 (0.870)	ICC = 0.448 (0.100) [− 0.266, 0.856]	ICC = 0.619 (0.100) [− 0.726, 0.922]	476 [− 178, 1130]	− 1236 [− 1890, − 581]
LIN	20,778 ± 560 [20310, 21247]	20,281 ± 458 [19898, 20663]	− 498 ± 440 [− 866, − 130]	$t_{(7)} = -3.198$ p=0.015 (1.131)	ICC = 0.343 (0.169) [− 0.378, 0.818]	ICC = 0.511 (0.169) [− 1.215, 0.900]	365 [− 295, 1025]	− 1361 [− 2021, − 701]
Predictors group 2	3000 m–5000 m–10,000 m–21097.5 m							
PL	20,778 ± 560 [20310, 21247]	20,845 ± 469 [20454, 21237]	67 ± 480 [− 335, 469]	$t_{(7)} = 0.395$ p=0.075 (0.140)	ICC = 0.604 (0.034) [− 0.056, 0.094]	ICC = 0.753 (0.034) [− 0.118, 0.950]	1009 [289, 1728]	− 874 [− 1594, − 155]
HYP	20,778 ± 560 [20310, 21247]	20,741 ± 493 [20329, 21154]	− 37 ± 515 [− 468, 394]	$t_{(7)} = -0.203$ p=0.845 (0.072)	ICC = 0.568 (0.046) [− 0.110,0.894]	ICC = 0.725 (0.046) [− 0.248, 0.944]	973 [201, 1745]	− 1047 [− 1819, − 275]
LIN	20,778 ± 560 [20310, 21247]	20,813 ± 491 [20403, 21224]	35 ± 505 [− 387, 457]	$t_{(7)} = 0.196$ p=0.085 (0.069)	ICC = 0.584 (0.040) [− 0.087, 0.898]	ICC = 0.737 (0.040) [− 0.190, 0.946]	1025 [268, 1782]	− 955 [− 1712, − 198]
Predictors group 3	3000 m–5000 m–10,000 m							
PL	20,778 ± 560 [20310, 21247]	21,108 ± 517	330 ± 487 [− 77, 737]	$t_{(7)} = 1.917$ p=0.097 (0.678)	ICC = 0.491 (0.078) [− 0.215, 0.870]	ICC = 0.658 (0.078) [− 0.548, 0.930]	1284 [554, 2013]	− 624 [− 1353, 105]
HYP	20,778 ± 560 [20310, 21247]	21,571 ± 526 [20676, 21540] [21132, 22011]	793 ± 474 [397, 1189]	$t_{(7)} = 4.735$ p=0.002 (1.674)	ICC = 0.073 (0.417) [− 0.593, 0.700]	ICC = 0.137 (0.417) [− 2.910, 0.824]	1722 [1012, 2432]	− 135 [− 845, 574]
LIN	20,778 ± 560 [20310, 21247]	21,612 ± 534 [21165, 22058]	833 ± 460 [448, 1218]	$t_{(7)} = 5.120$ p=0.001 (1.810)	ICC = 0.057 (0.433) [− 0.603, 0.692]	ICC = 0.108 (0.433) [− 3.039, 0.818]	1735 [1046, 2425]	− 69 [− 759, 621]

$\overline{X}$ mean value, *SD* standard deviation, *95% CI* 95% confident intervals ([lower, upper]), Δ_{abs} predicted–actual performance, ICC intra-class correlation coefficient ($ICC_{(1,1)}$: model 1 = one-way random, type 1 = reliability of single measures; $ICC_{(1,2)}$: model 1, type 2 = reliability of the mean measure); *LoA* upper and lower limits of agreements for the concordance plot (bias ± 1.96SD)

Discussion

To the best of our knowledge, this is the first study investigating the predictive accuracy of the PL, HYP and LIN models on 1-h track running performance in elite athletes, as well as analyzing the pacing profile and running pattern during this type of running events. The main findings showed that: (1) the use of different predictors may affect the estimation of the models' coefficients and the prediction of the elite 1-h track running performance in all the models; (2) the PL model provides a better predictive accuracy of the elite 1-h track running performance compared to the HYP and LIN models, for which reasonable predictions were observed only when the half-marathon was considered as the longest event among the models predictors; (3) CS_{Hyp} and CS_{Lin} seem to be highly dependent on the predictors chosen, and they corresponded to 96–98% of the average speed of the longest event considered as a predictor. Both CS_{Hyp} and CS_{Lin} did not correlate with the elite 1-h track running performance, whereas a moderate-to-strong positive correlation between PL_{V20} and 1-h performance was observed; (4) the men's best two 1-h track running performances of all times were run

Table 5 Actual and predicted performance, Δ_{abs}, magnitude of Δ_{abs}, ICC and concordance plot limits of agreement for the power law (PL), 2-parameter hyperbolic (HYP), and the linear (LIN) models

n = 9	Actual performance	Predicted performance	Δ_{abs}	Magnitude of Δ_{abs}	$ICC_{(1,1)}$	$ICC_{(1,2)}$	Concordance plot LoA	
Model	$\overline{X}\pm$SD (m) [95% CI]	$\overline{X}\pm$SD (m) [95% CI]	$\overline{X}\pm$SD (m) [95% CI]	*t*- and *p*-value (Cohen's *d*)	ICC (*p*-value) [95% CI]	ICC (*p*-value) [95% CI]	Upper (m) [95% CI]	Lower (m) [95% CI]
Predictors group 4	5000 m–10,000 m–21,097.5 m–42195 m							
PL	20,787 ± 525 [20384, 21190]	20,681 ± 438 [20344, 21017]	− 106 ± 417 [− 427, 215]	$t_{(8)}=0.763$ $p=0.468$ (0.254)	ICC = 0.641 (0.018) [0.054, 0.904]	ICC = 0.781 (0.018) [0.103, 0.950]	712 [142, 1282]	− 924 [− 1494, − 354]
HYP	20,787 ± 525 [20384, 21190]	20,413 ± 442 [20072, 20753]	− 374 ± 460 [− 728, − 21]	$t_{(8)}=-2.441$ $p=0.040$ (0.814)	ICC = 0.380 (0.128) [− 0.297, 0.813]	ICC = 0.551 (0.128) [− 0.844, 0.897]	527 [− 101, 1155]	− 1276 [− 1904, − 648]
LIN	20,787 ± 525 [20384, 21190]	20,303 ± 460 [19949, 20657]	− 484 ± 457 [− 836, − 133]	$t_{(8)}=-3.177$ $p=0.013$ (1.059)	ICC = 0.291 (0.195) [− 0.385, 0.776]	ICC = 0.451 (0.195) [− 1.252, 0.874]	412 [− 212, 1036]	− 1380 [− 2004, − 756]
Predictors group 5	5000 m–10,000 m–21,097.5 m							
PL	20,787 ± 525 [20384, 21190]	20,803 ± 435 [20468, 21137]	16 ± 470 [− 345, 377]	$t_{(8)}=0.101$ $p=0.922$ (0.034)	ICC = 0.566 (0.037) [− 0.064, 0.880]	ICC = 0.723 (0.037) [− 0.138, 0.936]	936 [295, 1578]	− 905 [− 1546, − 264]
HYP	20,787 ± 525 [20384, 21190]	20,743 ± 458 [20391, 21095]	− 44 ± 481 [− 414, 326]	$t_{(8)}=-0.274$ $p=0.791$ (0.091)	ICC = 0.561 (0.038) [− 0.072, 0.879]	ICC = 0.718 ((0.038) [− 0.155, 0.935]	900 [242, 1557]	− 988 [− 1645, − 330]
LIN	20,787 ± 525 [20384, 21190]	20,780 ± 457 [20429, 21131]	− 7 ± 478 [− 374, 360]	$t_{(8)}=-0.044$ $p=0.966$ (0.015)	ICC = 0.570 (0.035) [− 0.058, 0.882]	ICC = 0.726 (0.035) [− 0.123, 0.937]	929 [277, 1581]	− 943 [− 1595, − 291]
Predictors group 6	10,000 m–21,097.5 m–42,195 m							
PL	20,787 ± 525 [20384, 21190]	20,715 ± 422 [20391, 21039]	− 72 ± 414 [− 391, 246]	$t_{(8)}=-0.522$ $p=0.616$ (0.174)	ICC = 0.646 (0.017) [0.063, 0.906]	ICC = 0.785 (0.017) [0. 118, 0.951]	740 [174, 1306]	− 884 [− 1450, − 318]
HYP	20,787 ± 525 [20384, 21190]	20,547 ± 420 [20224, 20869]	− 240 ± 449 [− 585, 105]	$t_{(8)}=-1.605$ $p=0.147$ (0.535)	ICC = 0.495 (0.063) [− 0.162, 0.856]	ICC = 0.662 (0.063) [− 0.387, 0.922]	640 [27, 1253]	− 1120 [− 1734, − 507]
LIN	20,787 ± 525 [20384, 21190]	20,473 ± 425 [20146, 20799]	− 314 ± 433 [− 647, 19]	$t_{(8)}=-2.176$ $p=0.061$ (0.725)	ICC = 0.463 (0.078) [− 0.201, 0.845]	ICC = 0.633 (0.078) [− 0.504, 0.916]	535 [− 57, 1126]	− 1163 [− 1754, − 572]

$\overline{X}$ mean value, *SD* standard deviation, *95% CI* 95% confident intervals ([lower, upper]), Δ_{abs} predicted–actual performance, ICC intra-class correlation coefficient ($ICC_{(1,1)}$: model 1 = one-way random, type 1 = reliability of single measures; $ICC_{(1,2)}$: model 1, type 2 = reliability of the mean measure), *LoA* upper and lower limits of agreements for the concordance plot (bias ± 1.96SD)

at an even pace and very small but significant changes of both step length and step frequency were observed over time.

Prediction of 1-h track running performance

The prediction accuracy of the PL model was found to be remarkably high, suggesting that this model can offer a reasonable prediction of elite 1-h track running performance. Indeed, regardless of the model predictors used, a good agreement between predicted and actual performance was observed, even though the use of short predictor may lead to overestimate performance predictions. Although the effect of using different groups of predictors to estimate 1-h track running performance is rather small, they may modify the PL model coefficients (Fig. 1). This is in line with previous studies, which suggested that at least two PL models would operate in describing the speed loss over distance in running world records [18, 40] (i.e., fractal component of running performance phenomenon [3, 40]). It is worth noting that only running world records were used in these studies, and therefore, future investigations are required to verify whether this phenomenon is likewise present at an individual level.

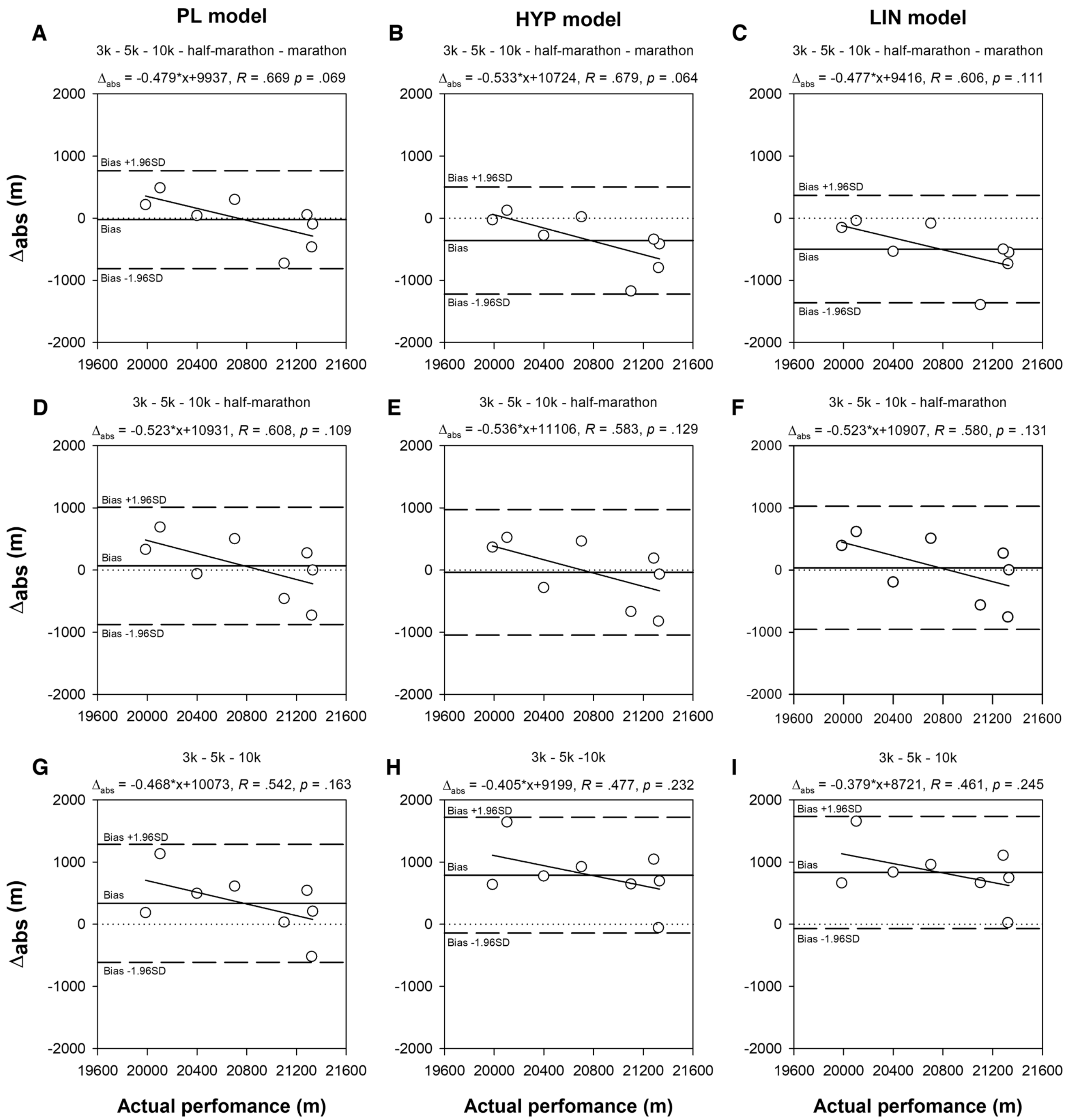

Fig. 2 Concordance plots for the PL (panels **C**, **F** and **I**), HYP (panels **B**, **E** and **H**) and LIN (panels **C**, **F** and **I**) models when the predictors group 1 (top panels), 2 (middle panels) and 3 (bottom panels) were used. Concordance plots depict the bias (i.e., the average value of Δ_{abs}, solid line) and the limits of agreement (bias ± 1.96SD, long-dashed lines) for each predictive model. Each panel shows the relationship between Δ_{abs} and actual performances along with the equation found. Data points represent the athletes

When the HYP and LIN models were used, a completely different scenario appeared. Indeed, substantial changes in performance prediction were observed when different predictors groups were used, and a good agreement between predicted and actual performance was obtained only when the predictors groups 2 and 5 were used. Moreover, CS_{Hyp} and CS_{Lin} estimates increased with short-event PB and decreased with longer event PB, and vice versa for ARC_{Hyp} and ARC_{Lin} estimates (Fig. 1). These findings are in line with previous studies, where changes in model coefficients were observed when using different model predictors, even when using those within the severe-intensity domain

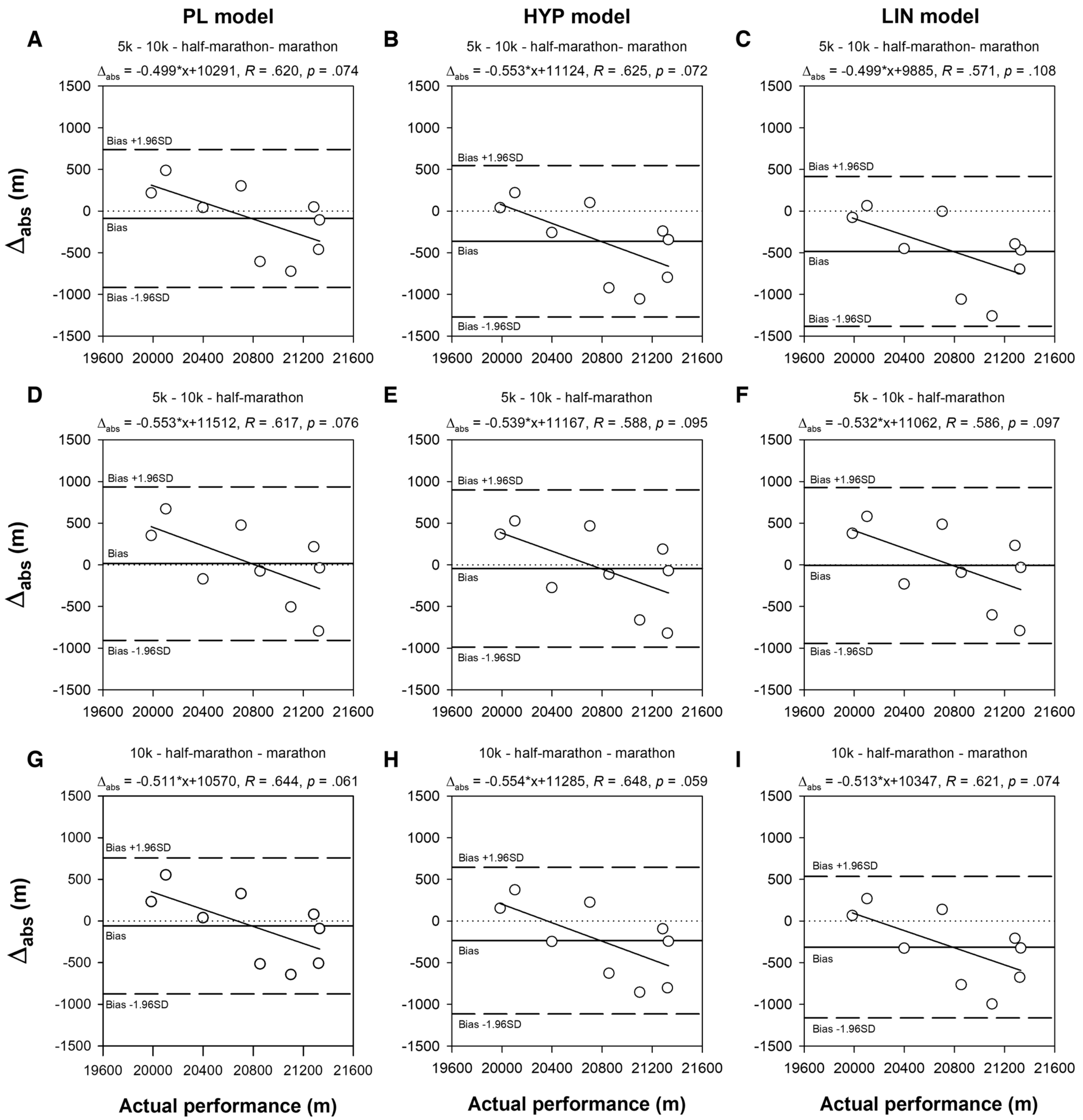

Fig. 3 Concordance plots for the PL (panels **A**, **D** and **G**), HYP (panels **B**, **E** and **H**) and LIN (panels **C**, **F** and **I**) models when the predictors group 4 (top panels), 5 (middle panels) and 6 (bottom panels) were used. Concordance plots depict the bias (i.e., the average value of Δ_{abs}, solid line) and the limits of agreement (bias ± 1.96SD, long-dashed lines) for each predictive model. Each panel shows the relationship between Δ_{abs} and actual performances along with the equation found. Data points represent the athletes

[32–34]. In this regard, it has been suggested that critical speed (*CS*) is highly dependent on the longest event chosen as a predictor, corresponding to the 95–99% of the average running speed of that event [33]. In line with this, we found that CS_{Hyp} and CS_{Lin} corresponded to the 96–98% of the average running speed of the longest event chosen. Overall, our findings showed that the HYP and LIN models do not reliably predict elite 1-h track running performance, and this

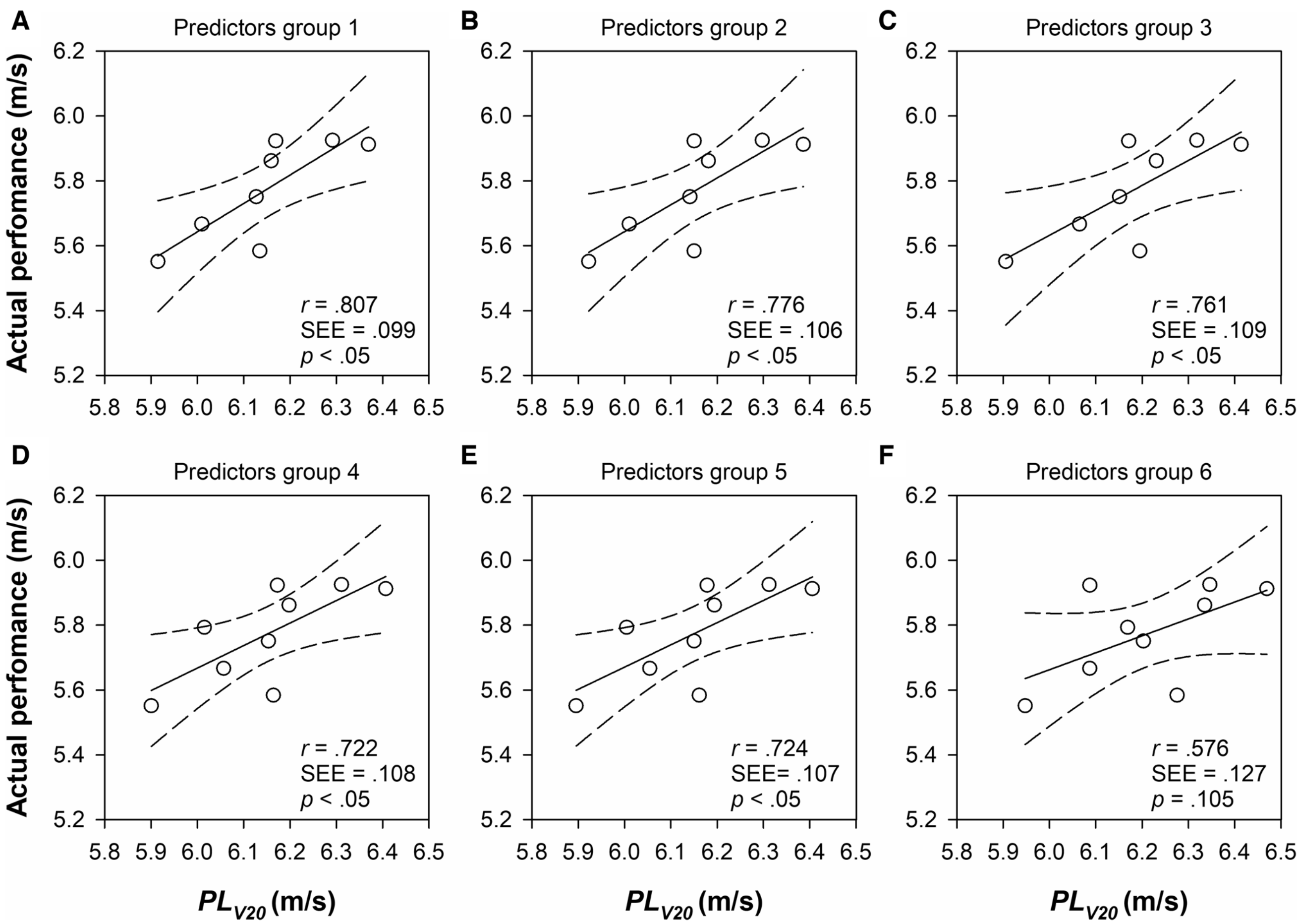

Fig. 4 Relationship between PL_{V20} and actual 1-h track running performance across the predictors groups. Data points represent the athletes. The regression line (solid line) and its 95% CI (short-dashed lines) are reported in each panel (*SEE* standard error of the estimate)

is consistent with Gamelin and colleagues study [12] who reported similar outcomes for amateur runners.

These findings collectively suggest that the PL model may offer a better performance prediction of elite 1-h track running performance compared to the HYP and LIN models. A potential explanation could be that the PL model can better characterize the individual running speed–distance profile compared to the HYP and LIN models. This is also suggested by a lower MAPE observed for the PL model. This may be due to the fact that the HYP model mathematically characterizes the intensity–duration relationship using an asymptotic value called *CS* [1, 10, 14, 41], not present in the PL model [14]. On the other hand, the assumption of a linear distribution between running distance and speed in the LIN model might be too simplistic from a predictive perspective, which may explain why this model could not provide a reasonable prediction. However, we cannot exclude that the HYP and LIN models may better predict the performance of other types of running events, such as those lasting between 2 and 15 min or included between 800 and 10,000 m, as previously suggested [1, 37].

The moderate-to-strong positive correlation between PL_{V20} and actual performance indicates that PL_{V20} is a better marker of endurance capacity compared to the more popular CS_{Hyp} and CS_{Lin}, for which no association with actual performance was found. In line with this, we also observed that, regardless of the predictors groups used, PL_{V20} strongly correlated with the average running speed of the models' predictors and its running speed values differed from both CS_{Hyp} and CS_{Lin}. Therefore, despite CS has traditionally been recognized as an important physiological determinant of endurance performance [1, 5, 9, 10, 42] and used to estimate endurance capacity [1, 6, 9], the present results indicate that it can be considered neither a valid predictor of running exhaustion time [41] or a good marker of endurance capacity in the elite athletes population. Although these findings suggest that PLv_{20} may be used as a better indicator of endurance capacity among elite runners, this is a new measure/marker and further investigation is required to better understand its applicability.

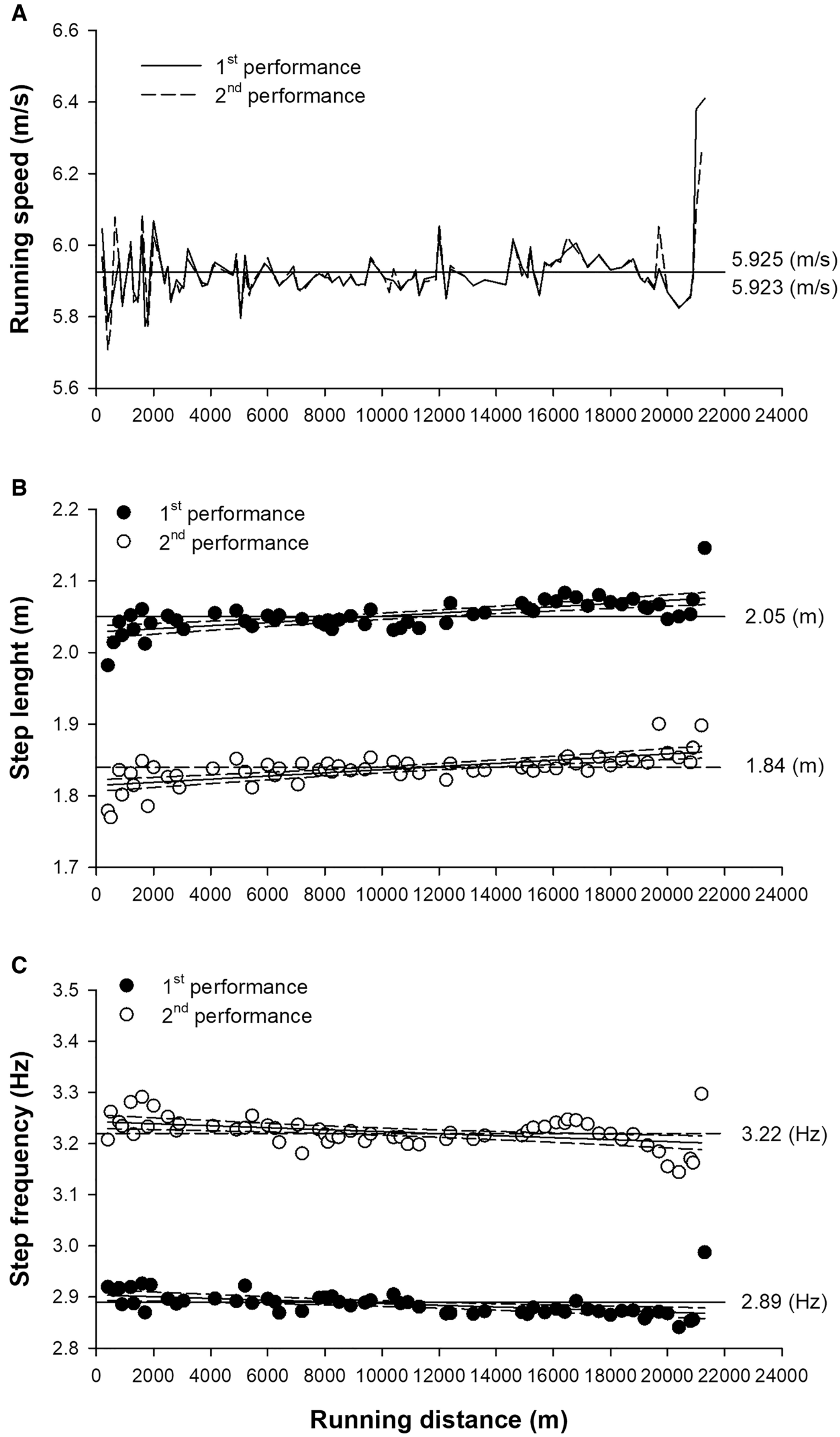

Fig. 5 Pacing profile (panel **A**), step length (panel **B**) and step frequency (panel **C**) of the 1st and 2nd best 1-h track running performance. 1st best performance = continued line and filled circles; 2nd best performance = dashed line and open circles. To note, significant slight increments and decrements over time were found for step length and step frequency, respectively, in both athletes (see text for more details)

The present findings raise legitimate uncertainties about the use of the HYP and LIN models in real settings, and the physiological meaning addressed to their coefficients (i.e., the anaerobic work capacity (AWC) and CS). First, using different predictors has a profound impact on the estimation of both AWC and CS [22, 32–34], which questions their physiological interpretations. Second, the fact that physical exhaustion occurs at exercise intensities below CS invalidates the definition of CS as an exercise intensity that can be sustained for an indefinite time [9, 10]. Likewise, the assumption that CS would represent the transition between the heavy and severe-intensity domain is questioned by the fact that its value seems to be highly dependent on the predictors chosen, even when selected within the severe-intensity domain [22, 32–34]. Third, the HYP model is unable to provide an accurate description of the whole spectrum of the exercise intensity–duration relationship, and this is very evident for performances lasting longer than 25–30 min [33, 43]. On the other hand, there are several data—the present ones included—suggesting that the PL model would be able to pursue this aim [18, 33, 40]. Fourth, it is worth noting that the horizontal asymptotic value for the PL model (i.e., the analogous value of the CS) corresponds to zero. This implies that the exercise intensity that can be theoretically sustained for an indefinite time does not exist for the PL model, challenging the physiological meaning classically addressed to the CS [33]. Taken together, these data raise questions about the classical physiological meaning of AWC and CS as well and their practical applications.

Pacing profile and running pattern of the all-time men's best two 1-h track running performances

An even pacing strategy has been proposed as optimal for track running events between 1.5 km and 10 [4], and in longer distances [24]. Similarly, our findings revealed an even pacing profile (with an end-spurt) for both the first and second best 1-h track running performances of all times. It is important to note that the analyzed 1-h track running event was performed with pacemakers until ~ 11,800 m, and that a light pacemaker on the left side of lane 1 constantly indicated the world record pace to break. These factors indicate that an even pacing strategy was most likely decided in advance, suggesting that coaches and athletes may also believe the even pacing strategy to be the optimal one.

Pacing profile can be different between competitions as athletes may focus on competitive tactics or best performance strategies [27]. Specifically, the finishing position is generally the most important outcome in high-standard competitions (e.g., World Championships and Olympic games) compared to other events (e.g., National/International meetings), where the finishing time might be more relevant. It has previously been observed that when endurance runners are focused on the finishing time, an even pace is adopted during distance-based events [27]. In the present study, the same pacing profile was found in athletes aiming at breaking the 1-h track running world record, supporting the notion that an even pace may also be preferred during time-based events. These findings highlight the crucial need to define a priori the pacing strategy to adopt. In this context, the PL model may be used for this purpose.

There is a current lack of information about how well athletes are able to set themselves an effective running pace for time-based events. Unlike a distance-based running event, where there is continuous visual feedback of progress, time is a more abstract intangible construct which, as has been previously demonstrated in children [44], may be more difficult to set an anticipatory pace even for experienced runners. However, it is still unclear how the temporal and spatial information inputs are perceived by runners and what is their role in the anticipatory pacing. Hence, further investigation is required.

Changes in running pace during competitions are caused by changes in step length and/or frequency. In the present study, the running pattern of the first and second best 1-h track running performance did not considerably change, except for the final end-spurt during which both step length and frequency increased. Interestingly, both athletes slightly increased the step length and decreased the step frequency over the race, but the running pace did not vary. These minimal changes in the running pattern are consistent with previous findings [45–48], and may have been caused by the development of central and/or peripheral fatigue [49]. These results may underline a potential locomotor strategy adopted by the athletes to overcome fatigue and avoid or minimize decrements in running speed. However, due to the nature of the present study, it was not possible to identify the underlying mechanisms.

The best 1-h track running performance was characterized by longer step lengths and lower step frequencies compared to the second-best performance (see Fig. 5). Longer step lengths are generally associated with greater running performances in both sprints [50–52] and endurance running events [30, 45, 48], while no direct relation has been observed for higher step frequencies [30, 51, 52]. In line with this, the present findings would also support the notion that step length may be the key variable for succeeding in endurance running events. However, since the current analysis was performed on two athletes only, further studies on 1-h track running events are certainly required.

Limitations and methodological considerations

The PB times considered were performed at different periods of the athletes' career, often several years before they achieved their best performance in the 1-h track running (see Table 1). Although no correlation between Δ_{abs} and Δ_T was found, this may have introduced an error in the performance estimates. Indeed, it is important to note that the individual running speed–duration profile is not constant in time and can vary during athletes' career and training periods. Therefore, a more valid performance prediction may be obtained using performance data closer in time to the event that needs to be predicted.

The video analysis was performed using a video recorded at a relatively low sampling rate (25 fps), which may have introduced an error associated with the running time estimation. However, the error magnitude—if present—was limited to few photograms only (i.e., ≤ 2 photograms, corresponding to ≤ 0.08 s), unlikely affecting the interpretation of the present findings. Moreover, the number of steps done within the portions of track considered was computed using a single video containing videos recorded from different cameras placed around the athletic track. This might have also generated some estimation error in the number of steps. However, the researchers who computed the analysis reported that—if present—this error was very low within each portion of track analyzed (i.e., unlikely higher than 2/10 of one running step) and not expected to affect the interpretation of the findings.

We tested a relatively small sample size of elite runners, which might expose the analysis to an increased type II error. Therefore, further powered studies involving primary data analysis are certainly required to confirm the present findings.

Practical applications

The present findings reveal that using athletes' PB together with the PL model can offer a reasonable prediction of elite 1-h track running performance and characterize individual intensity–duration profiles. Although we used elite runners' PB performances, the approach presented herein is also expected to be applicable to sub-elite and amateur runners. Moreover, some data suggest that the PL model may also provide a reasonable prediction of other endurance running events [14, 22]; however, further investigations are required.

Smyth and colleagues [11] showed that using the LIN model together with daily training data recorded from wearable devices in endurance runners would allow to predict marathon performance and pacing. However, the present findings suggest that the PL model might also be used in association with daily training data, favoring thus its implementation and use within sport devices and wearables. Nevertheless, further studies are required to investigate the applicability and use of the PL model, and standard methodological procedures should be identified.

The present findings also suggest that an even pacing strategy may be the optimal strategy during 1-h track running events. This implies that knowing a priori the most sustainable running speed to adopt during this kind of running events may be very important. By providing a good estimation of 1-h track running performance, the PL model can help athletes and coaches to identify the optimal pacing strategy to adopt during these events.

Conclusions

The present study shows that the PL model can offer a better prediction of the elite 1-h track running performance compared to the HYP and LIN models. Data also suggest that the PL model would better characterize the individual intensity–duration profile of elite endurance runners. PL_{v20} may be used as an indicator of endurance capacity in the elite runners population. CS_{Hyp} and CS_{Lin} seem to be highly dependent on the predictors chosen, raising legitimate concerns about their physiological meaning. An even pacing profile with an end-spurt was observed in the first and second best 1-h track running performances of all times, supporting the notion that an even pace might be the best strategy for this type of events. A slight tendency in increasing the step length and decreasing the step frequency over the race was observed. Further studies are required to better understand the link between fatigue and running pattern as well as to optimize the use of the PL model in the context of endurance performance prediction.

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Availability of data and materials The data sets generated during and/or analysed during the current study are available from the corresponding author on reasonable request. PB performances for each athlete are provided in Table 1.

Code availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in this study were in accordance with the ethical standards of the institutional and/or national research committee (Ethics Committee of the University of Essex, ID: ETH2021-0765) and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent Not applicable.

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