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, PLV20 (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
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 \( \alpha \) 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.
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 least-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

| Athlete | 3000 m | 5000 m | 10,000 m | Half marathon | Marathon | 1-h (m) |
|---------|-------|-------|---------|--------------|---------|--------|
| 1       | 6.63  | 6.47  | 6.22    | 5.91         | 5.62    | 21.330 |
|         | 452.6 | 773.1 | 1606.6  | 3572.0       | 7511.0  |        |
| Date     | 2016  | 2011  | 2011    | 2015         | 2018    | 2020   |
| 2       | 6.52  | 6.37  | 6.04    | 5.69         | 5.63    | 21.322 |
|         | 460.4 | 784.9 | 1656.4  | 3710.0       | 7489.0  |        |
| Date     | 2015  | 2018  | 2014    | 2017         | 2020    | 2020   |
| 3       | 6.74  | 6.58  | 6.32    | 5.97         | 5.58    | 21.285 |
|         | 445.1 | 759.4 | 1582.8  | 3535.0       | 7556.0  |        |
| Date     | 1998  | 1998  | 1998    | 2006         | 2006    | 2007   |
| 4       | 6.58  | 6.35  | 6.14    | 5.67         | 5.24    | 21.101 |
|         | 455.7 | 787.8 | 1628.2  | 3723.0       | 8049.0  |        |
| Date     | 1989  | 1989  | 1989    | 1988         | 1986    | 1991   |
| 5       | 6.08  | 5.96  | 5.76    | 5.24         | 20.855  |        |
|         | 823.0 | 1679.2| 3664.0  | 8059.0       |         |        |
| Date     | 1987  | 1987  | 1987    | 1987         | 1989    | 1990   |
| 6       | 6.35  | 6.25  | 6.08    | 5.88         | 5.59    | 20.703 |
|         | 472.6 | 800.2 | 1644.8  | 3588.0       | 7548.0  |        |
| Date     | 2017  | 2017  | 2019    | 2017         | 2017    | 2020   |
| 7       | 6.27  | 6.20  | 5.97    | 5.58         | 5.37    | 20.399 |
|         | 478.2 | 806.8 | 1675.2  | 3783.0       | 7851.0  |        |
| Date     | 1999  | 1994  | 1996    | 1996         | 1995    | 1996   |
| 8       | 6.48  | 6.28  | 6.12    | 5.72         | 5.39    | 20.102 |
|         | 463.0 | 795.7 | 1633.5  | 3686.0       | 7833.0  |        |
| Date     | 1999  | 1998  | 1999    | 2008         | 2004    | 2009   |
| 9       | 6.20  | 5.98  | 5.82    | 5.65         | 5.37    | 19.985 |
|         | 483.8 | 836.6 | 1719.1  | 3735.0       | 7863.0  |        |
| Date     | 2012  | 2013  | 2014    | 2018         | 2019    | 2020   |
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 \( D_{PL} = \sqrt[3]{3600c} \), where \( D_{PL} \) is the predicted running distance, \( c \) and \( a \) the coefficients of the PL model.

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

The individual running speed–distance profile obtained using the LIN model (i.e., \( D_{Lin} = CSH_{Lin} \times t + ARC_{Lin} \)), where \( CSH_{Lin} \) is the critical speed, \( ARC_{Lin} \) 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, \( \Delta_{Abs} \)] and [the time interval between when the 1-h track PB was performed and the mean time of when the predictor events were performed, \( \Delta_{T} \)] 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 \( PL_{v20} \)) was computed as \( PL_{v20} = PL_{d20} / 1200 \), where \( PL_{d20} \) corresponds to \( PL_{d20} = \sqrt[3]{1200c} \). Subsequently, \( PL_{v20} \) was compared with \( CSHyp \) and \( CSLin \) 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, \( PL_{v20} \), and performance estimates. A two-way repeated measures ANOVA (3 × 6) was used to investigate the difference between \( CSHyp \), \( CSLin \) and \( PL_{v20} \) across predictors groups. In the case of a significant interaction, only planned follow-up comparisons were performed (i.e., comparisons between \( CSHyp \), \( CSLin \) vs \( PL_{v20} \) 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
performance can be considered a gold standard measure, we plotted Δabs 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 PLv20 and actual performance were evaluated using r. The relationship between models’ coefficients, PLv20 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 (ηp²) 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).

### Table 2 Model’s coefficients, adjusted R² (R² 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 | R² adj | MAPE | Correlation with actual performance | Correlation with predictors’ average speed |
|-------|-----------------------|-----------------------|--------|------|-------------------------------------|------------------------------------------|
|       | X ± SD [95% CI] | X ± SD [95% CI] | X ± SD [95% CI] | X ± SD [95% CI] | r (p value) | r (p value) | r (p value) | r (p value) |
| Model |                       |                       |         |      |                                      |                                          |
| PL    | 10.835 ± 1.248         | -0.063 ± 0.011        | 0.971 ± 0.014 | 0.003 ± 0.001 | 0.971 (0.21) | − 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 1
Δt = 4.0 ± 2.4

| 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 2
Δt = 4.5 ± 2.9

| 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] |                       |                                          |

Predictors group 3
Δt = 5.2 ± 3.7

| PL   | 9.370 ± 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] |                       |                                          |

X mean value, SD standard deviation, 95% CI 95% confident intervals ([lower, upper]), MAPE mean absolute percentage error, r Pearson’s correlation coefficient, Δt 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.
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 $\Delta_{abs}$ and $\Delta_1$ was found for all the investigated models and predictors (0.226 ≤ $r$ ≤ 0.484; 0.221 ≤ $p$ ≤ 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 and models are reported in Tables 4 and 5.

Regardless of the predictors group used, no significant differences when using the PL model (all Benjamini–Hochberg’s $p > 0.05$). No differences were also found for $\text{PL}_v^{20}$ (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 correlation between the follow-up comparisons, where no differences were observed for $c$, $\alpha$ and performance predictions when using the PL model (all Benjamini–Hochberg’s $p > 0.054$). No differences were also found for $\text{PL}_v^{20}$ (all Benjamini–Hochberg’s $p > 0.064$).

The average running speed corresponding to $\text{PL}_v^{20}$ was found equal to 6.15 ± 0.14 m·s$^{-1}$ in the predictors group 1, 6.15 ± 0.15 m·s$^{-1}$ in the predictors group 2, 6.18 ± 0.15 m·s$^{-1}$ in the predictors group 3, 6.15 ± 0.15 m·s$^{-1}$ in the predictors group 4, 6.15 ± 0.15 m·s$^{-1}$ in the predictors group 5, 6.21 ± 0.16 m·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 $\text{PL}_v^{20}$ and $\text{CS}_{\text{Hyp}}$ 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 $\text{PL}_v^{20}$ and $\text{CS}_{\text{Lin}}$ 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 $\text{PL}_v^{20}$ 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 $\text{PL}_v^{20}$ and the actual 1-h track running performance is shown in Fig. 4. To note, positive high correlations between $\text{PL}_v^{20}$ and the actual 1-h track running performances were observed, except when the predictors group 6 was used. Conversely, no associations between $\text{CS}_{\text{Hyp}}$, $\text{CS}_{\text{Lin}}$ 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·s$^{-1}$, coefficient of variation (CV) = 1.5%, median = 5.913 m·s$^{-1}$, range = [5.774, 6.410]; 2nd: 5.923 ± 0.074 m·s$^{-1}$, CV = 1.2%, median = 5.912 m·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%]).
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 = −0.0000046, 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. \( ^5 p < 0.05 \) 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. \( \text{CS}_{\text{hyp}} \) and \( \text{CS}_{\text{lin}} \) 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, \( \Delta_{\text{abs}} \), magnitude of \( \Delta_{\text{abs}} \), 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 | \( \Delta_{\text{abs}} \) | Magnitude of \( \Delta_{\text{abs}} \) | ICC \((p\text{-value)}) | ICC \((p\text{-value})\) | Concurrency plot LoA |
|-----|-------------------|----------------------|-------------------------|-------------------------|-----------------------|-----------------------|----------------------|
|     | \( \bar{X} \pm SD \) (m) | \( \bar{X} \pm SD \) (m) | \( \bar{X} \pm SD \) (m) | \((R\text{-value})\) | ICC \((p\text{-value})\) | ICC \((p\text{-value})\) | Upper (m) | Lower (m) |
|     | [95% CI] | [95% CI] | [95% CI] | | [95% CI] | [95% CI] | [95% CI] | [95% CI] |
| PL  | 3000 m–5000 m | 20,778 ± 560 | 20,736 ± 438 | −43 ± 400 | \( t_{(2)} = -0.301 \) \( p = 0.107 \) | ICC = 0.515 \((p = 0.041)\) | [0.141, 0.934] | [0.247, 0.966] | [741, 142, 1340] | [−826, −1425, −227] |
| HYP | 30,000 m–10,000 m | 20,778 ± 560 | 20,398 ± 436 | −380 ± 437 | \( t_{(2)} = -2.462 \) \( p = 0.043 \) | ICC = 0.448 \((p = 0.100)\) | [0.266, 0.856] | [−0.726, 0.922] | [476, 1236] | [−178, 1130] | [−1890, −581] |
| LIN | 20,778 ± 560 | 20,281 ± 458 | −498 ± 400 | 386 ± 130 | \( t_{(2)} = -3.198 \) \( p = 0.015 \) | ICC = 0.343 \((p = 0.169)\) | [0.378, 0.818] | [−1.215, 0.900] | [365, 1361] | [−295, 1025] | [−2021, −701] |

\( \bar{X} \) mean value, SD standard deviation, 95% CI 95% confidence intervals ([lower, upper]), \( \Delta_{\text{abs}} \) 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) \( CS_{\text{Hyp}} \) and \( CS_{\text{Lin}} \) 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 \( CS_{\text{Hyp}} \) and \( CS_{\text{Lin}} \) 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, $\Delta_{\text{abs}}$, magnitude of $\Delta_{\text{abs}}$, ICC and concordance plot limits of agreement for the power law (PL), 2-parameter hyperbolic (HYP), and the linear (LIN) models

| Model | Predictors | Actual performance ($\bar{X} \pm \text{SD (m)}$ [95% CI]) | Predicted performance ($\bar{X} \pm \text{SD (m)}$ [95% CI]) | $\Delta_{\text{abs}}$ ($\bar{X} \pm \text{SD (m)}$ [95% CI]) | Magnitude of $\Delta_{\text{abs}}$ t- and p-value (Cohen's d) | ICC of $\Delta_{\text{abs}}$ ($p$-value) [95% CI] | ICC of $\Delta_{\text{abs}}$ ($p$-value) [95% CI] | Concordance plot LoA Upper (m) [95% CI] | Lower (m) [95% CI] |
|-------|-------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| PL    | group 4     | 5000 m–10,000 m–21,097.5 m–42,195 m              |                                                 |                                                 |                                                 |                                                 |                                                 |                                                 |                                                 |
|       |             | 20,787 ± 525 [20384, 21190]                     | 20,681 ± 438 [20344, 21017]                     | $-106 \pm 417 [-427, 215]$                     | $t_{0.025} = 0.763$ p = 0.468 (0.254)             | ICC = 0.641 (0.018) [0.054, 0.904]                 | ICC = 0.731 (0.018) [0.103, 0.950]                 | 712 [142, 1282]                                  | $-924 [-1494, -354]$                             |
| HYP   |             | 20,787 ± 525 [20384, 21190]                     | 20,413 ± 442 [20072, 20753]                     | $-374 \pm 460 [-728, -21]$                     | $t_{0.025} = -2.441$ p = 0.040 (0.814)            | ICC = 0.380 (0.128) [0.297, 0.813]                 | ICC = 0.511 (0.128) [0.484, 0.897]                 | 527 [$-101, 1155$]                               | $-1276 [-1904, -648]$                           |
| LIN   |             | 20,787 ± 525 [20384, 21190]                     | 20,303 ± 460 [19949, 20657]                     | $-484 \pm 457 [-836, -133]$                    | $t_{0.025} = -3.177$ p = 0.013 (1.059)            | ICC = 0.291 (0.195) [0.385, 0.776]                 | ICC = 0.451 (0.195) [1.252, 0.874]                 | 412 [$-212, 1036$]                               | $-1380 [-2004, -756]$                           |
|       | group 5     | 5000 m–10,000 m–21,097.5 m                      |                                                 |                                                 |                                                 |                                                 |                                                 |                                                 |                                                 |
| PL    |             | 20,787 ± 525 [20384, 21190]                     | 20,803 ± 435 [20468, 21137]                     | $16 \pm 470 [-345, 377]$                       | $t_{0.025} = 0.101$ 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]                     | $-44 \pm 481 [-414, 336]$                      | $t_{0.025} = -0.274$ 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]                     | $-7 \pm 478 [-374, 360]$                      | $t_{0.025} = -0.044$ p = 0.966 (0.015)            | ICC = 0.570 (0.035) [0.058, 0.882]                 | ICC = 0.726 (0.035) [0.123, 0.937]                 | 929 [$277, 1581$]                               | $-943 [-1595, -291]$                            |
|       | group 6     | 10,000 m–21,097.5 m–42,195 m                    |                                                 |                                                 |                                                 |                                                 |                                                 |                                                 |                                                 |
| PL    |             | 20,787 ± 525 [20384, 21190]                     | 20,715 ± 422 [20391, 21039]                     | $-72 \pm 414 [-391, 246]$                      | $t_{0.025} = -0.522$ p = 0.616 (0.174)            | ICC = 0.646 (0.017) [0.065, 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]                     | $-240 \pm 449 [-585, 105]$                     | $t_{0.025} = -1.605$ 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]                     | $-314 \pm 433 [-647, 19]$                      | $t_{0.025} = -2.176$ p = 0.061 (0.725)            | ICC = 0.463 (0.078) [0.201, 0.845]                 | ICC = 0.633 (0.078) [0.504, 0.916]                 | 535 [$-57, 1126$]                               | $-1163 [-1754, -572]$                           |

$\bar{X}$ mean value, SD standard deviation, 95% CI 95% confidence intervals ([lower, upper]), $\Delta_{\text{abs}}$ 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).
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, $C_{Hyp}$ and $C_{Lin}$ 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. 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 $\Delta_{abs}$, solid line) and the limits of agreement (bias ± 1.96SD, long-dashed lines) for each predictive model. Each panel shows the relationship between $\Delta_{abs}$ and actual performances along with the equation found. Data points represent the athletes.
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$_{\text{Hyp}}$ and CS$_{\text{Lin}}$ 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

![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 $\Delta_{\text{abs}}$, solid line) and the limits of agreement (bias ± 1.96SD, long-dashed lines) for each predictive model. Each panel shows the relationship between $\Delta_{\text{abs}}$ and actual performances along with the equation found. Data points represent the athletes [32–34].](image)
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 PLv20 and actual performance indicates that PLv20 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, PLv20 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 PLv20 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.

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**Fig. 4** Relationship between PLv20 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).
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 $\Delta_{\text{obs}}$ and $\Delta_T$ 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. PLv20 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.

### Author contributions

Conception or design of the work: MG, CG, LS, SMM, and DM. Acquisition, analysis or interpretation of data for the work: MG, CG, LS. MG wrote the first draft of the manuscript. All the Authors revisited the work critically for important intellectual content. All authors approved the final version of the manuscript and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. All persons designated as authors qualify for authorship, and all those who qualify for authorship are listed.

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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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References

1. Jones AM, Vanhatalo A (2017) The, “critical power” concept: applications to sports performance with a focus on intermittent high-intensity exercise. Sports Med 47:65–78
2. Joyner MJ (2017) Physiological limits to endurance exercise performance: influence of sex. J Physiol 595:2949–2954
3. Katz JS, Katz L (1999) Power laws and athletic performance. J Sports Sci 17:467–476
4. Tucker R, Lambert MI, Noakes TD (2006) An analysis of pacing strategies during men’s world-record performances in track athletics. Int J Sports Physiol Perform 1:233–245
5. Jones AM, Kirby BS, Clark IE, Rice HM, Fulkerson E, Wylie LJ et al. (2021) Physiological demands of running at 2-hour marathon race pace. J Appl Physiol 130:369–379
6. Billat LV, Koralisztein JP, Morton RH (1999) Time in human endurance models. Sports Med 27:359–379
7. Bosquet L, Duchene A, Lecot F, Dupont G, Leger L (2006) Vmax estimate from three-parameter critical velocity models: validity and impact on 800 m running performance prediction. Eur J Appl Physiol 97:34–42
8. Bundle MW, Hoyt RW, Weyand PG (2003) High-speed running performance: a new approach to assessment and prediction. J Appl Physiol 95:1955–1962
9. Poole DC, Burnley M, Vanhatalo A, Rossiter HB, Jones AM (2016) Critical power. Med Sci Sports Exerc 48:2320–2334
10. Jones AM, Vanhatalo A, Burnley M, Morton RH, Poole DC (2010) Critical power: implications for determination of VO2max and exercise tolerance. Med Sci Sports Exerc 42:1876–1890
11. Smyth B, Muniz-Pumares D (2020) Calculation of critical speed from raw training data in recreational marathon runners. Med Sci Sports Exerc 52:2637–2645
12. Gamelin FX, Coquart JM, Ferranti N, Vodougnon H, Matran R, Leger L et al. (2006) Prediction of one-hour running performance using constant duration tests. J Strength Cond Res 20:735–739
13. Bosquet L, Léger L, Legros P (2002) Methods to determine aerobic endurance. Sports Med 32:675–700
14. Vandewalle H (2018) Modelling of running performances: comparisons of power-law, hyperbolic, logarithmic, and exponential models in elite endurance runners. Biomed Res Int 2018:8203062
15. Casado A, Hanley B, Jiménez-Reyes P, Renfree A (2020) Pacing profiles and tactical behaviors of elite runners. J Sport Health Sci. https://doi.org/10.1016/j.jshs.2020.06.011
16. Díaz JJ, Fernández-Ozcorra EI, Torres M, Santos-Concejero J (2019) Men vs. women world marathon records’ pacing strategies from 1998 to 2018. Eur J Sport Sci 19:1297–1302
17. Kennelly AE (1906) An approximate law of fatigue in the speeds of racing animals. Proc Am Acad Arts Sci 42:275–331
18. Savaglio S, Carbone V (2000) Scaling in athletic world records. Nature 404:244
19. Zinoubi B, Vandewalle H, Zbidi S, Driss T (2019) Estimation of running endurance by means of empirical models: a preliminary study. Sci Sports 34:24–29
20. Vandewalle H (2017) Mathematical modeling of the running performances in endurance exercises: comparison of the models of Kennelly and Péronnet-Thibaut for World records and elite endurance runners. Am J Eng Res 6:317–323
21. Kosmidis I, Passfield L (2015) Linking the performance of endurance runners to training and physiological effects via multi-resolution elastic net. arXiv preprint arXiv:150601388. http://arxiv.org/abs/1506.01388
22. Zinoubi B, Vandewalle H, Driss T (2017) Modeling of running performances in humans: comparison of power laws and critical speed. J Strength Cond Res 31:1859–1867
23. Muniz-Pumares D, Karsten B, Triska C, Glaister M (2019) Methodological approaches and related challenges associated with the determination of critical power and curvature constant. J Strength Cond Res 33:584–596
24. Abbiss CR, Laursen PB (2008) Describing and understanding pacing strategies during athletic competition. Sports Med 38:239–252
25. Tucker R (2009) The anticipatory regulation of performance: the physiological basis for pacing strategies and the development of a perception-based model for exercise performance. Br J Sports Med 43:392–400
26. Hanley B (2015) Pacing profiles and pack running at the IAAF World Half Marathon Championships. J Sports Sci 33:1189–1195
27. Thiel C, Foster C, Banzer W, De Koning J (2012) Pacing in Olympic track races: competitive tactics versus best performance strategy. J Sports Sci 30:1107–1115
28. Paululo J, Amnio G, Migliaccio GM, D’ottavio S, Tihanyi J (2012) Kinematics of running at different slopes and speeds. J Strength Cond Res 26:1331–1339
29. Clermont CA, Osis ST, Phinyomark A, Ferber R (2017) Kinematic gait patterns in competitive and recreational runners. J Appl Biomech 33:268–276
30. Ogueta-Alday A, Morante JC, Gómez-Molina J, García-López J (2018) Similarities and differences among half-marathon runners according to their performance level. PLoS ONE 13:e0191688
31. Schache AG, Blanch PD, Rath DA, Wrigley TV, Starr R, Bennell KL (2001) A comparison of overground and treadmill running for measuring the three-dimensional kinematics of the lumbo–pelvic–hip complex. Clin Biomech 16:667–680
32. Bishop D, Gjengenius D, Howard A et al. (1998) The critical power function is dependent on the duration. Int J Sports Med 19:125–129
33. Gorostiaga EM, Sánchez-Medina L, García-Tabar I (2021) Overtraining and exercise tolerance. Med Sci Sports Exerc 53:278–284
34. Triska C, Karsten B, Beedic C, Koller-Zeisler B, Nimmerrichter A, Tschán H (2018) Different durations within the method of best practice affect the parameters of the speed–duration relationship. Eur J Sport Sci 18:332–340
35. Levenberg K (1944) A method for the solution of certain nonlinear problems in least squares. Quart Appl Math 2:164–168
36. Marquardt DW (1963) An algorithm for least-squares estimation of nonlinear parameters. J Soc Ind Appl Math 11:431–441
37. Jones AM, Burnley M, Black MI, Poole DC, Vanhatalo A (2019) The maximal metabolic steady state: redefining the "gold standard." Physiol Rep 7:e14098
38. Krouwer JS (2008) Why Bland–Altman plots should use X, not (Y+X)/2 when X is a reference method. Stat Med 27:778–780
39. Bland JM, Altman DG (1999) Measuring agreement in method comparison studies. Stat Methods Med Res 8:135–160
40. García-Manso JM, Martín-González JM, Vaamonde D, Silva-Grigoletto MED (2012) The limitations of scaling laws in the prediction of performance in endurance events. J Theor Biol 300:324–329
41. Vandewalle H, Vautier JF, Kachouri M, Lechevalier JM, Monod H (1997) Work-exhaustion time relationships and the critical power concept. A critical review. J Sports Med Phys Fit 37:89–102
42. Mitchell EA, Martin NRW, Bailey SJ, Ferguson RA (2018) Critical power is positively related to skeletal muscle capillarity and type I muscle fibers in endurance-trained individuals. J Appl Physiol 125:737–745
43. Péronnet F, Thibault G (1989) Mathematical analysis of running performance and world running records. J Appl Physiol 67:453–465
44. Chinnasamy C, St Clair Gibson A, Micklewright D (2013) Effect of spatial and temporal cues on athletic pacing in schoolchildren. Med Sci Sports Exerc 45:395–402
45. Williams KR, Snow R, Agruss C (1991) Changes in distance running kinematics with fatigue. J Appl Biomech 7:138–162
46. Hanley B, Mohan AK (2014) Changes in gait during constant pace treadmill running. J Strength Cond Res 28:1219–1225
47. Hunter I, Smith GA (2007) Preferred and optimal stride frequency, stiffness and economy: changes with fatigue during a 1-h high-intensity run. Eur J Appl Physiol 100:653–661
48. Enomoto Y, Kadono H, Suzuki Y, Chiba T, Koyama K (2008) Biomechanical analysis of the medalists in the 10,000 metres at the 2007 World Championships in Athletics. New Stud Athl 3:61–66
49. Azevedo RDA, Silva-Cavalcante MD, Lima-Silva AE, Bertuzzi R (2021) Fatigue development and perceived response during self-paced endurance exercise: state-of-the-art review. Eur J Appl Physiol 121:687–696
50. Krzysztof M, Mero A (2013) A kinematics analysis of three best 100 m performances ever. J Hum Kinet 36:149–160
51. Weyand PG, Sterlign DB, Bellizzi MJ, Wright S (2000) Faster top running speeds are achieved with greater ground forces not more rapid leg movements. J Appl Physiol 89:1991–1999
52. Weyand PG, Sandell RF, Prime DNL, Bundle MW (2010) The biological limits to running speed are imposed from the ground up. J Appl Physiol 108:950–961

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