



Original article

Profiling elite male 100-m sprint performance: The role of maximum velocity and relative acceleration

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Abstract

Purpose: This study aimed to determine the accuracy of a 4 split time modelling method to generate velocity-time and velocity-distance variables in elite male 100-m sprinters and subsequently to assess the roles of key sprint parameters with respect to 100-m sprint performance. Additionally, this study aimed to assess the differences between faster and slower sprinters in key sprint variables that have not been assessed in previous work.

Methods: Velocity-time and velocity-distance curves were generated using a mono-exponential function from 4 split times for 82 male sprinters during major athletics competitions. Key race variables—maximum velocity, the acceleration time constant (τ), and percentage of velocity lost (v_{Loss})—were derived for each athlete. Athletes were divided into tertiles, based on 100-m time, with the first and third tertiles considered to be the faster and slower groups, respectively, to facilitate further analysis.

Results: Modelled split times and velocities displayed excellent accuracy and close agreement with raw measures (range of mean bias was -0.2% to 0.2% , and range of intraclass correlation coefficients (ICCs) was 0.935 to 0.999) except for 10-m time (mean bias was $1.6\% \pm 1.3\%$, and the ICC was 0.600). The 100-m sprint performance time and all 20-m split times had a significant near-perfect negative correlation with maximum velocity ($r \geq -0.90$) except for the 0 to 20-m split time, where a significantly large negative correlation was found ($r = -0.57$). The faster group had a significantly higher maximum velocity and τ ($p < 0.001$), and no significant difference was found for v_{Loss} ($p = 0.085$).

Conclusion: Coaches and researchers are encouraged to utilize the 4 split time method proposed in the current study to assess several key race variables that describe a sprinter's performance capacities, which can be subsequently used to further inform training.

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Keywords: Deceleration; Modelling; Race phases; Reaction time; Split times

1. Introduction

The 100-m sprint can be divided into 3 main phases: the block start with acceleration phase, which is sometimes subdivided into initial acceleration and main acceleration phase (or pick-up); the maximum velocity phase; and the deceleration phase.^{1–4} Plotting a sprinter's velocity-distance curve (Fig. 1) allows each distinct phase of the 100 m to be identified. Initial acceleration is represented by a rapid increase in velocity,² whereas a more gradual increase in velocity (pick-up phase) is subsequently observed.^{4,5} The maximum velocity phase is

characterized by a gradual increase in velocity, which is represented as a relatively flat section of the velocity-distance curve, where the velocity remains close to 100% of maximum velocity (v_{max}).⁶ Sprinters typically reach their highest speed between 50 m and 80 m, with faster sprinters usually reaching v_{max} later in the race.^{7–9} During the deceleration phase, sprinters attempt to counteract the inevitable decrease in velocity due to fatigue and maintain the highest velocity possible for the remainder of the race.⁹ This is represented by a gradual decrease in velocity, usually over the final 20 m, and that can be assessed by calculating the percentage of velocity lost (v_{Loss}) relative to v_{max} .¹⁰

A sprinter's position-time and velocity-time curves can be modelled throughout the acceleration phase of a sprint by using a mono-exponential function.^{11–14} This function

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requires 2 input parameters: the sprinter's maximal horizontal velocity (v_{hmax}) and the acceleration time constant (τ), which is the ratio of v_{hmax} to the initial horizontal acceleration.¹³ The variable τ represents the total delay in overcoming inertia up to the instant maximum velocity is achieved;¹¹ thus, its measurement unit is the second. For example, if a sprinter reached v_{hmax} at 40 m during a sprint with a τ value of 1 s, this means that the sprinter would cover this 40-m distance 1 s faster if there were no lag due to inertia (i.e., no acceleration phase). If τ were equal to zero, the sprinter would instantaneously reach maximal velocity without any acceleration phase, which is obviously not possible. Consequently, a more practical description is that τ represents an athlete's relative acceleration ability, with lower values indicating the ability to reach a higher percentage of v_{max} more quickly relative to athletes with a higher τ .¹⁵ Despite the identification of τ as a performance factor in sprinting, the specific influence of τ on 100-m performance in elite male sprinters has yet to be determined.

Several methods exist for modelling horizontal position-time and velocity-time from split times using the mono-exponential function. Furusawa et al.¹¹ reported a mean difference of 0.079 m between the raw position data of a sprinter, collected at 10 points during a 54.9-m (60-yard) sprint, and the position estimated by the mono-exponential function. Clark et al.¹⁵ demonstrated that 3 split times recorded at 9.1, 18.3, and 36.6 m in National Football League (NFL) Combine athletes could be used to generate accurate distance-time, velocity-time, and velocity-distance curves over 36.6 m (40 yards) using the mono-exponential equation. Samozino et al.¹⁶ demonstrated the validity of a 5 split zone method, where timing gates were set up at 10, 15, 20, 30, and 40 m to assess position-time and velocity-time curves in sprinters, and the researchers subsequently used these data to model power and force properties. Furusawa et al.,¹¹ Samozino et al.,¹⁶ and Clark et al.¹⁵ demonstrated the ability of the mono-exponential function to model position-time and velocity-time curves accurately over short sprints (<55 m). Consequently, accurate derivation of horizontal position-time and velocity-time curves during the acceleration phase of a 100 m sprint with the fewest possible number of split times would be of considerable practical benefit to sprint coaches and researchers alike.

The limited availability of large numbers of world-class athletes is often a problem for researchers seeking to conduct research that informs elite performance. This is understandable, especially in the 100-m sprint, because elite athletes often train in small, highly specialized groups dispersed throughout the world, with sprint coaches who dedicate a significant amount of time and investment in order to provide a high-quality coaching services. Using publicly available competition sprint data, usually in the form of sprint split times collected at major events by independent researchers or International Association of Athletics Federations (IAAF) biomechanical research teams, provide a potential solution to this problem. Online, publicly available data sets have been widely used in 100-m sprint research to assess the impact of rule changes,¹⁷ the effects of wind speed,¹⁸ age, and sex differences in sprint mechanical properties,⁹ and reaction times,¹⁹ stride kinematics,⁸ and kinetics and energetics of world-class

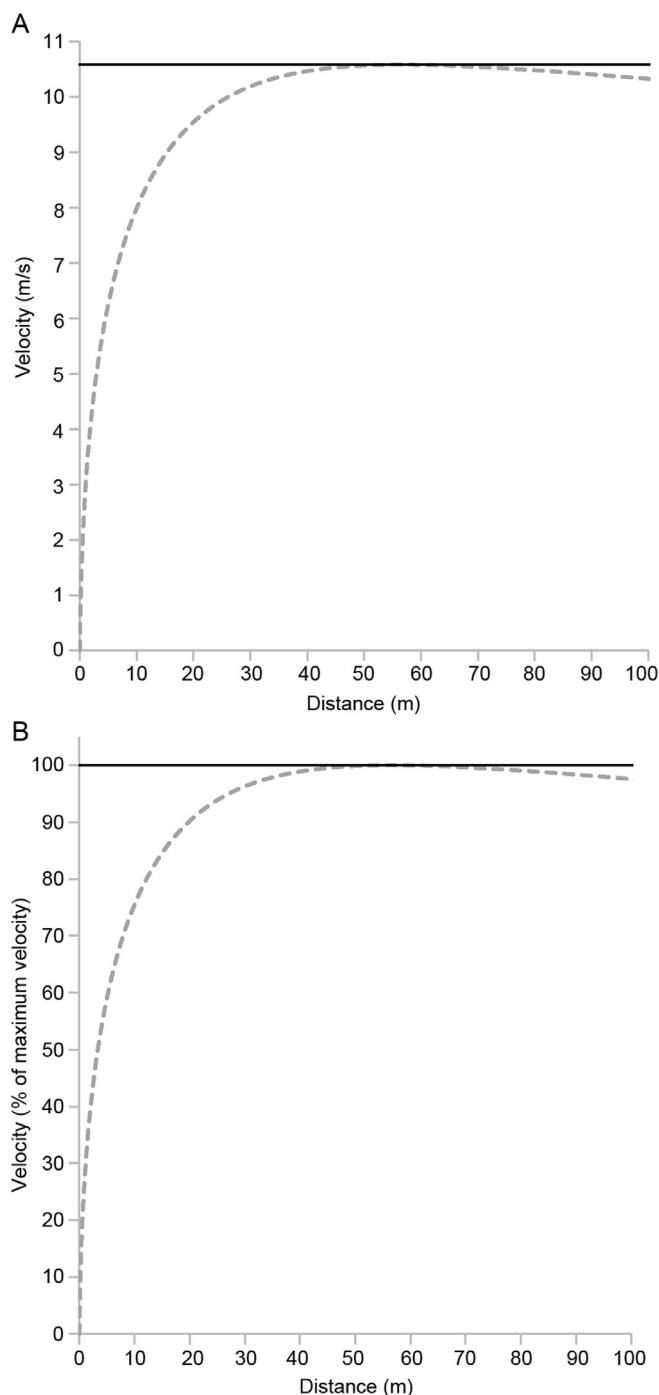


Fig. 1. An example of how velocity, in absolute units (A) and as a percentage of maximum velocity (B), changes throughout a 100-m sprint. In both plots, the broken grey line represents the modelled velocity-distance curves, and the black line represents maximum velocity. A rapid increase followed by a gradual increase in velocity can be observed over the first 40 m. Subsequently, maximum velocity is attained and maintained until the final section of the 100-m race, where velocity begins to decrease.

performers.^{20–22} Consequently, examination of sprint acceleration and velocity profiles using these data sources has the potential to provide greater insight into world-class sprint performance.

This study aimed to determine the accuracy of a 4 split time modelling method to generate velocity-time and velocity-

distance variables in elite 100-m male sprinters using publicly available sprint data from major international sprint events. A subsequent aim was to assess the roles of key sprint parameters— v_{\max} , τ , and v_{Loss} —in 100-m sprint performance and to subsequently assess the role of v_{\max} in each phase of the 100-m sprint. Finally, this study aimed to compare faster and slower sprinters using modelled and measured race variables.

2. Methods

2.1. Subjects

The data used in this study were obtained from online position-time records taken during major athletic competitions, with 82 male sprint athletes included in the final analysis. Athletes were subsequently divided into tertiles to facilitate further analysis. Tertiles were selected based on 100-m time, with the first and third tertiles considered the faster and slower groups, respectively. Tertiles were used so that there was a clear distinction between the faster and slower groups. This prevented the possibility of border cases (i.e., instances where athletes are only 0.01–0.02 s away from being considered “faster” instead of “slower” or *vice versa*). The 2017 IAAF scoring tables of athletics were used to score each 100-m sprint time, enabling future comparisons between performances achieved in the current study and performances by female 100-m sprinters or performances in other sprint events (e.g., 60 m and 200 m). Mean \pm SD 100-m time, anthropometric data, and IAAF points were obtained for all sprinters, faster sprinters, and slower sprinters (Table 1). The collection and analysis of the data in this study was approved by the University of Limerick Research Ethics committee.

2.2. Data sources

Sprint data were available from IAAF-accredited biomechanics projects and additional research published by research groups utilizing video analysis. In total, data were publicly available for 8 world championships between 1987 and 2017^{1,8,23–28} and 3 Olympic Games between 1988 and 2012.^{8,29} Athletes were included in the analysis only if their entire 100-m data were available, either as 10-m or 20-m split times, and if their reaction time were available via IAAF-approved start information systems. Additionally, video footage of each race was assessed by the primary investigator to ensure that each athlete included in the final

analysis completed his 100-m sprint without sustaining an injury or intentionally slowing down before the finish line. Only the athletes' best performances in all competitions were retained for analysis. The championships, methods employed, split times recorded, and number of athletes retained for the final analysis are described in Table 2. These data were recorded using a mixture of high-speed video measurements (sampling rates: 50–250 Hz) and laser analysis (sampling rates: 50–100 Hz), which have been demonstrated to yield comparable results.^{20,30}

2.3. Sprint analysis

To ensure consistency in the analysis, all data were presented in 20-m split times so that 0–20, 20–40, 40–60, 60–80, and 80–100-m data were available for all athletes. The following variables were included in the final analysis based on these raw position-time data: 100-m sprint performance (excluding reaction time), reaction time, and 20-m split times expressed as raw times and as percentages of 100-m time, v_{\max} , and the average velocity achieved over the 0–20 m and 20–40 m sections expressed as a percentage of v_{\max} . The v_{\max} was calculated as 20 m divided by the fastest 20-m split time achieved in the race. Additionally, the v_{Loss} was determined as an indicator of the athlete's ability to maintain maximum velocity during the final 20 m of the race.¹⁰ The v_{Loss} was calculated as v_{\max} minus average velocity over the final phase of the race divided by maximum velocity multiplied by 100, or simply:

$$v_{\text{Loss}} = \frac{v_{\max} - \left(\frac{20 \text{ m}}{80-100 \text{ m time}} \right)}{v_{\max}} \times 100 \quad (1)$$

The first 4 split times (minus reaction time), representing the acceleration phase of the 100-m sprint, were subsequently used to generate horizontal position of the centre of mass (x_h) vs. time (t) curves for each athlete using a mono-exponential function:¹⁶

$$x_h(t) = v_{\text{hmax}} \times \left(t + \tau \times e^{-\frac{t}{\tau}} \right) - v_{\text{hmax}} \times \tau \quad (2)$$

where v_{hmax} is the estimated maximum horizontal velocity achieved, t is time, e is the natural exponential, and τ is the acceleration time constant. Using Eq. 2 above and the Microsoft Excel solver function, the best estimations for τ and v_{hmax} were calculated using a least squares approach between the raw position-time data and the modelled position-time data similar to previous investigations.^{9,16} The estimated τ values were retained for the final analysis whereas the estimated v_{hmax} values were used only to compare against the raw v_{\max} values, which were retained for the final analysis.

Using the approximated values of v_{hmax} and τ , the velocity of the athlete's centre of mass vs. time curves could be generated by differentiating Eq. 2 with respect to time:

$$v_h(t) = v_{\text{hmax}} \times \left(1 - e^{-\frac{t}{\tau}} \right) \quad (3)$$

The velocity achieved at 20 m and 40 m was estimated for each athlete by using the generated velocity-time curves and was expressed as a percentage of v_{\max} , which is similar to the work of Clark et al.,¹⁵ e is the natural exponential.

Table 1

Descriptive statistics (mean \pm SD) for all ($n = 82$), faster ($n = 28$), and slower ($n = 28$) sprinters (mean \pm SD).

	All	Faster	Slower
100 m time (s)	10.17 \pm 0.23	9.91 \pm 0.10	10.43 \pm 0.09
Range (s)	9.58 – 10.59	9.58 – 10.02	10.27 – 10.59
Age (year)	25 \pm 3	26 \pm 4	24 \pm 3
Height (m)	1.80 \pm 0.06	1.81 \pm 0.06	1.79 \pm 0.06
Mass (kg)	77.1 \pm 7.4	78.3 \pm 6.6	76.1 \pm 8.0
IAAF points	1151 \pm 78	1238 \pm 35	1063 \pm 28

Abbreviation: IAAF = International Association of Athletics Federations.

2.4. Statistical analysis

The accuracy of the 4 split time modelling technique was evaluated through several methods. First, the 4 measured split times used to generate the model (20, 40, 60, and 80 m) were compared with modelled times ($n = 82$). Second, where available, measured split times at 10, 30, 50, and 70 m were compared with modelled times ($n = 33$). Finally, measured and modelled average velocities over 0–20 m, 20–40 m, 40–60 m, and 60–80 m, in addition to v_{\max} values, were compared ($n = 82$). Bland-Altman 95% limits of agreement analysis³¹ and intraclass correlation coefficients (ICCs) (2,1) with 95% confidence intervals (CIs)³² were used to compare modelled and measured variables.

The normality of the data was assessed by plotting and visually inspecting the shape of the histograms for all variables and by using the Shapiro Wilks test with the α level set at $p < 0.05$. Differences in all sprint measures between faster and slower groups were assessed using independent samples t tests. The Cohen d effect sizes (ES) were calculated and were interpreted as trivial ($ES < 0.2$), small ($0.2 \geq ES < 0.6$), moderate ($0.6 \geq ES < 1.2$), large ($1.2 \geq ES < 2$), very large ($2 \geq ES < 4$), or extremely large (≥ 4) according to the scale proposed by Hopkins et al.³³

Relationships between measures were assessed using the Pearson correlation coefficient or the Spearman rank correlation coefficient with 95% CIs. Partial correlations were used to assess the relationships between τ and 100-m sprint performance and between v_{Loss} and 100-m sprint performance while controlling for v_{\max} . The strengths of the correlations were evaluated as trivial (0–0.09), small (0.10–0.29), moderate (0.30–0.49), large (0.50–0.69), very large (0.70–0.89), near perfect (0.90–0.99), or perfect (1).³³ All statistical analyses were completed using SPSS (Version 24.0, IBM, Armonk, NY, USA). As multiple t tests and correlations were performed, the familywise error rate was controlled at 0.05 by using a false-discovery rate controlling procedure.³⁴

3. Results

The results of the comparison between measured and modelled variables are given in Table 3. All variables displayed

Table 2
Competition sources of sprint data, measurement methods employed, and reported split time intervals

Competition	Measurement method	Reported splits (number of athletes)
Olympic Games Seoul 1988	Video analysis	10 m (4)
World Championships Tokyo 1991	Video analysis	10 m (6)
World Championships Athens 1997	Laser	10 m (4)
World Championships Seville 1999	Video analysis	10 m (7)
World Championships Osaka 2007	Video analysis	10 m (3)
World Championships Berlin 2009	Video analysis & laser	20 m (49); 10 m (3)
World Championships London 2017	Video analysis	10 m (6)

excellent accuracy and close agreement with the raw measures (range of mean bias was -0.2% to 0.2% , and range of ICCs was 0.935 to 0.999) except for the 10-m time, which had a mean bias of $1.6\% \pm 1.3\%$ and an ICC of 0.600.

Descriptive statistics (mean \pm SD), mean differences, and effect sizes between faster and slower groups are provided in Table 4. The faster group had a significantly faster 100-m sprint performance times (extremely large effect) and shorter reaction times (moderate effect) and were faster over all sections of the 100 m (very large to extremely large effects). Relative to the slower group, the faster group spent a significantly higher percentage of time in the 0–20 m (large effect) and 20–40 m (moderate effect) sections, whereas the slower group spent a significantly higher percentage of time in the 40–60 m (large effect), 60–80 m (small effect) and 80–100 m (moderate effect) sections. No significant difference was found for relative percentage of reaction times.

The faster group also had a significantly higher v_{\max} (very large effect) and significantly lower velocity, as a percentage of v_{\max} , at 20 m and 40 m (large effects) and a significantly lower average velocity, as a percentage of v_{\max} , over the 0–20 (large effect) m and 20–40 m sections (moderate effect). A significantly higher τ was found in the faster group (moderate effect), whereas a small effect was found for v_{Loss} , with the faster group displaying lower values; however, this was not significant ($p = 0.085$).

The relationships between v_{\max} , 0–20, 20–40, 40–60, 60–80, and 80–100-m sprint times are shown in Table 5. All 20-m split times had a significant, near-perfect negative correlation with v_{\max} except for the 0–20 m split time, which had a significantly large negative correlation with v_{\max} .

Scatterplots illustrating the relationship between τ , 20-m, and 40-m velocity and average velocity over 0–20-m and 20–40-m sections are given in Fig. 2. Significant, near perfect negative correlations were found between τ , velocity at 20 m, and 40 m, and average velocity over 0–20 m, whereas a significant, large negative correlation was found between τ and average velocity over 20–40 m.

Scatterplots illustrating the relationship between 100-m sprint performance, v_{\max} , τ , and v_{Loss} , along with the relationships between v_{\max} , τ , and v_{Loss} , are given in Fig. 3. Significant negative correlations were found between 100-m sprint performance and v_{\max} (near perfect) and τ (moderate). No significant relationship was found between 100-m sprint performance and v_{Loss} . A significant positive correlation was found between v_{\max} and τ (large), whereas no significant relationship was found between v_{\max} and v_{Loss} . After controlling for v_{\max} , a significant, very large positive correlation was found between 100-m sprint performance and τ ($r = 0.86$, 95%CI: 0.78–0.91, $p < 0.001$), whereas the correlation between 100-m sprint performance and v_{Loss} was not significant ($r = 0.14$, 95%CI: -0.10 to 0.37 , $p = 0.220$).

4. Discussion

4.1. Accuracy of the 4 split time modelling method

The results shown in Table 3 suggest that the 4 split time modelling method provided an accurate estimation of sprint times for every 10-m section from 20 m to 80 m, average

velocities for each 20 m section (0–20, 20–40, 40–60, and 60–80 m) and v_{\max} (ICCs: 0.935–0.999, mean bias: -0.2% to 0.2%). The curves generated by the modelling method were derived from 2 input parameters, v_{hmax} and τ . Only v_{hmax} could be compared to directly measured data (i.e., v_{\max}). To indirectly assess the accuracy of τ , sprint times, and velocities that were not directly used to generate the distance-time and velocity-time curves were evaluated. This approach was successful in demonstrating the accuracy of the 4 split time method except for the estimation of the 10-m time (ICC: 0.600, mean bias: 1.6%). This suggests some uncertainty in the accuracy of velocity estimates over the first 10 m; however, this could not be directly assessed using the available data.

This study used only elite male data; thus, the 4 split time method cannot be assumed to be as accurate for female sprinters or sprinters at lower performance levels. The mono-exponential function can model only the acceleration phase of a sprint; therefore, the accuracy may be affected due to differences in acceleration ability (e.g., time to reach v_{\max}), with elite male sprinters accelerating over a longer distance and for a longer time compared to their female and less skilled counterparts.^{2,4,7,9,35} Future research in female athletes is, therefore, warranted because other split combinations (e.g., 10 m, 20 m, 40 m, and 60 m) may be more appropriate. Additionally, it is recommended that coaches or researchers using the 4 split time modelling method on 100-m sprint data should assess the input (v_{\max}) and output data to confirm the accuracy of the method.

4.2. Differences between faster and slower sprinters

Faster sprinters had a significantly higher v_{\max} (6%) and a higher τ (4.3%) than slower sprinters (Table 4). The difference in v_{\max} was considered very large (ES = 3.69), whereas the difference in τ was considered moderate (ES = 0.81). This demonstrates that v_{\max} was the most important variable measured in

elite 100-m sprinters. The moderate differences in τ can likely be explained by the very large difference between groups in v_{\max} . Because τ represents the ratio of maximal horizontal velocity to the maximal horizontal acceleration, a higher v_{\max} without a proportional increase in maximal horizontal acceleration would result in a higher ratio and, thus, a higher τ . This finding is contrary to the results of Clark et al.,¹⁵ who found no significant difference in τ between NFL Combine athletes with higher v_{\max} and athletes with lower v_{\max} , even with very large differences in v_{\max} . Maximal horizontal acceleration can be assessed by dividing v_{\max} by τ . Utilizing the mean data reported in Clark et al.,¹⁵ maximal acceleration values of 12.49 m/s^2 and 11.07 m/s^2 were estimated for the faster and slower groups, respectively, representing a 1.41 m/s^2 (11.3%) mean difference. In contrast, maximal acceleration values of $9.92 \pm 0.35 \text{ m/s}^2$ and $9.75 \pm 0.43 \text{ m/s}^2$ were found for faster and slower sprinters, respectively, in the current study. This represents a mean difference of 0.17 m/s^2 (1.7%) and was not significant ($p = 0.105$).

A significant moderate difference was found for reaction times, with faster sprinters reacting 10.8% more quickly than slower sprinters (Table 4). This is supported by previous research, which found a significant, weak positive correlation ($r = 0.292$) between reaction times and 100-m sprint time in 674 male sprinters during IAAF athletic world championships.¹⁹ The faster sprinters were quicker over all 20-m sections; however, the mean differences were larger in the 40–60, 60–80, and 80–100-m sections (-6.6% , -5.9% , and -6.9% , respectively) relative to the 0–20 m and 20–40 m sections (-3.0% and -4.7% , respectively). This explains why the faster sprinters spent a significantly higher percentage of time in the 0–20 m and 20–40 m sections and a lower percentage of time in the 40–60, 60–80, and 80–100 m sections compared to the slower sprinters. These differences in absolute and relative times are not surprising because the faster and slower groups were initially created based on 100-m sprint performance times.

Table 3

Mean \pm SD results, mean bias \pm SD with 95% LOA, and single-measure ICC with 95%CI for measured and modelled sprint times and sprint velocities.

	Measured	Modelled	Mean bias \pm SD (95% LOA)	% Mean bias \pm SD (95% LOA)	ICC (95%CI)
Sprint times					
10 m (s)	1.752 \pm 0.039	1.779 \pm 0.030	0.028 \pm 0.023 (–0.018 to 0.073)	1.6 \pm 1.3 (–1.0 to 4.1)	0.600 (–0.044 to 0.846)
20 m (s)	2.817 \pm 0.047	2.820 \pm 0.047	0.002 \pm 0.008 (–0.014 to 0.018)	0.1 \pm 0.3 (–0.5 to 0.6)	0.985 (0.975–0.990)
30 m (s)	3.710 \pm 0.050	3.709 \pm 0.050	–0.001 \pm 0.011 (–0.022 to 0.020)	0.0 \pm 0.3 (–0.6 to 0.6)	0.977 (0.954–0.989)
40 m (s)	4.665 \pm 0.080	4.663 \pm 0.082	–0.002 \pm 0.008 (–0.017 to 0.013)	–0.1 \pm 0.2 (–0.4 to 0.3)	0.995 (0.993–0.997)
50 m (s)	5.467 \pm 0.067	5.465 \pm 0.066	–0.002 \pm 0.008 (–0.018 to 0.015)	0.0 \pm 0.2 (–0.3 to 0.3)	0.992 (0.984–0.996)
60 m (s)	6.441 \pm 0.128	6.440 \pm 0.125	–0.001 \pm 0.010 (–0.019 to 0.018)	0.0 \pm 0.2 (–0.3 to 0.3)	0.997 (0.996–0.998)
70 m (s)	7.186 \pm 0.087	7.196 \pm 0.089	0.005 \pm 0.007 (–0.008 to 0.019)	0.1 \pm 0.1 (–0.1 to 0.3)	0.995 (0.976–0.998)
80 m (s)	8.203 \pm 0.171	8.204 \pm 0.172	0.001 \pm 0.006 (–0.011 to 0.013)	0.0 \pm 0.1 (–0.1 to 0.2)	0.999 (0.999–0.999)
Sprint velocities					
0–20 m (m/s)	7.10 \pm 0.12	7.10 \pm 0.12	–0.01 \pm 0.02 (–0.05 to 0.03)	–0.1 \pm 0.3 (–0.6 to 0.5)	0.985 (0.975–0.990)
20–40 m (m/s)	10.83 \pm 0.24	10.85 \pm 0.25	0.03 \pm 0.08 (–0.14 to 0.19)	0.2 \pm 0.8 (–1.3 to 1.8)	0.935 (0.896–0.959)
40–60 m (m/s)	11.28 \pm 0.34	11.26 \pm 0.30	–0.01 \pm 0.08 (–0.17 to 0.15)	–0.1 \pm 0.7 (–1.5 to 1.3)	0.967 (0.950–0.979)
60–80 m (m/s)	11.36 \pm 0.32	11.35 \pm 0.33	–0.01 \pm 0.10 (–0.20 to 0.18)	–0.1 \pm 0.9 (–1.8 to 1.6)	0.955 (0.932–0.971)
Maximum velocity (m/s)	11.39 \pm 0.33	11.37 \pm 0.33	–0.02 \pm 0.07 (–0.15 to 0.11)	–0.2 \pm 0.6 (–1.3 to 1.0)	0.978 (0.966–0.986)

Note: 20, 40, 60, and 80 m splits ($n = 82$); 10, 30, 50, and 70 m splits ($n = 33$).

Abbreviations: CI = confidence interval; ICC = intraclass correlation coefficient; LOA = limits of agreement.

Table 4
Mean \pm SD for all sprinters ($n = 82$), faster sprinters ($n = 28$), and slower sprinters ($n = 28$), mean difference with 95%CI and Cohen d effect size for all sprint variables.

	All	Faster	Slower	Mean difference (95%CI)	% Mean difference (95%CI)	p	Cohen d (95%CI)
100-m sprint performance ^a (s)	10.02 \pm 0.23	9.77 \pm 0.10	10.28 \pm 0.09	-0.50 (-0.55 to -0.46)	-5.2 (-5.7 to -4.7)	<0.001**	-5.13 (-5.63 to -4.62)
v_{\max} (m/s)	11.39 \pm 0.33	11.71 \pm 0.18	11.02 \pm 0.17	0.70 (0.61 to 0.79)	6.0 (5.2 to 6.8)	<0.001**	3.69 (3.21 to 4.17)
τ (s)	1.17 \pm 0.07	1.18 \pm 0.06	1.13 \pm 0.06	0.05 (0.02 to 0.08)	4.3 (1.6 to 6.9)	0.002**	0.81 (0.31 to 1.31)
v_{Loss} (%)	3.30 \pm 1.23	2.87 \pm 1.30	3.37 \pm 0.78	-0.51 (-1.08 to 0.07)	-17.6 (-37.7 to 2.5)	0.085	-0.44 (-0.94 to 0.06)
Race sections ^b							
RT (s)	0.146 \pm 0.018	0.136 \pm 0.016	0.151 \pm 0.017	-0.015 (-0.024 to -0.006)	-10.8 (-17.3 to -4.3)	0.002**	-0.83 (-1.34 to -0.33)
0-20 m (s)	2.82 \pm 0.05	2.77 \pm 0.02	2.86 \pm 0.03	-0.08 (-0.10 to -0.07)	-3.0 (-3.5 to -2.5)	<0.001**	-2.96 (-3.47 to -2.46)
20-40 m (s)	1.85 \pm 0.04	1.81 \pm 0.02	1.89 \pm 0.02	-0.08 (-0.10 to -0.07)	-4.7 (-5.3 to -4.1)	<0.001**	-4.02 (-4.52 to -3.52)
40-60 m (s)	1.78 \pm 0.05	1.72 \pm 0.03	1.83 \pm 0.02	-0.11 (-0.13 to -0.10)	-6.7 (-7.5 to -5.9)	<0.001**	-4.24 (-4.74 to -3.74)
60-80 m (s)	1.76 \pm 0.05	1.72 \pm 0.03	1.82 \pm 0.03	-0.10 (-0.12 to -0.08)	-5.9 (-6.8 to -5.0)	<0.001**	-3.20 (-3.71 to -2.70)
80-100 m (s)	1.82 \pm 0.06	1.76 \pm 0.03	1.88 \pm 0.03	-0.12 (-0.14 to -0.10)	-6.9 (-7.9 to -5.8)	<0.001**	-3.32 (-3.82 to -2.82)
Relative race sections							
RT (%)	1.4 \pm 0.2	1.4 \pm 0.2	1.5 \pm 0.2	-0.1 (-0.2 to 0.0)	-5.3 (-11.5 to 1.0)	0.097	-0.42 (-0.92 to 0.08)
0-20 m (%)	27.7 \pm 0.4	28.0 \pm 0.3	27.4 \pm 0.4	0.6 (0.4 to 0.8)	2.1 (1.5 to 2.7)	<0.001**	1.66 (1.16 to 2.17)
20-40 m (%)	18.2 \pm 0.2	18.2 \pm 0.1	18.1 \pm 0.2	0.1 (0.02 to 0.2)	0.5 (0.1 to 1.0)	0.018*	0.61 (0.11 to 1.11)
40-60 m (%)	17.5 \pm 0.2	17.4 \pm 0.2	17.6 \pm 0.1	-0.2 (-0.3 to -0.2)	-1.4 (-1.8 to -0.9)	<0.001**	-1.52 (-2.03 to -1.02)
60-80 m (%)	17.3 \pm 0.2	17.3 \pm 0.2	17.4 \pm 0.2	-0.1 (-0.2 to -0.0)	-0.6 (-1.2 to -0.1)	0.034*	-0.54 (-1.04 to -0.04)
80-100 m (%)	17.9 \pm 0.3	17.8 \pm 0.2	18.0 \pm 0.2	-0.3 (-0.4 to -0.2)	-1.5 (-2.2 to -0.9)	<0.001**	-1.12 (-1.63 to -0.62)
Velocity							
Average velocity 0-20 m (% v_{\max})	62.4 \pm 1.5	61.6 \pm 1.1	63.6 \pm 1.3	-2.0 (-2.6 to -1.3)	-3.2 (-4.3 to -2.1)	<0.001**	-1.52 (-2.02 to -1.02)
Average velocity 20-40 m (% v_{\max})	95.1 \pm 1.5	94.6 \pm 1.2	96.0 \pm 1.5	-1.5 (-2.2 to -0.9)	-1.6 (-2.3 to -0.8)	<0.001**	-1.01 (-1.52 to -0.51)
20 m velocity (% v_{\max})	91.1 \pm 1.2	90.5 \pm 1.0	92.0 \pm 0.9	-1.5 (-2.0 to -1.0)	-1.7 (-2.3 to -1.2)	<0.001**	-1.56 (-2.06 to -1.06)
40 m velocity (% v_{\max})	98.2 \pm 0.5	97.9 \pm 0.4	98.5 \pm 0.3	-0.6 (-0.8 to -0.4)	-0.6 (-0.8 to -0.4)	<0.001**	-1.52 (-2.03 to -1.02)

Note: ^a100-m sprint time excluding reaction time; ^bmeasured times.

* $p \leq 0.05$; ** $p \leq 0.01$.

Abbreviations: CI = confidence interval; RT = reaction time; τ = acceleration time constant; v_{Loss} = percentage of maximum velocity lost in final 20 m; v_{\max} = measured maximum velocity.

The faster group had a 17.6% lower mean v_{Loss} than the slower group, although this difference was not statistically significant ($p = 0.085$) (Table 4). It is worth noting that a larger variance was recorded in the faster group (SD: $\pm 1.3\%$; range: 0.6%–5.6%) compared to the slower group (SD: $\pm 0.78\%$; range: 1.6%–5.2%). Consequently, future research with a larger sample would have greater statistical power to determine whether differences exist. Slawinski et al.⁹ found that world-class male sprinters had a significantly lower loss in relative velocity compared to world-class female sprinters. A potential explanation provided by the authors was that the women in that study reached v_{\max} earlier and thus had a deceleration phase that was 1.77 s longer than that of the men, which would lead to greater relative fatigue effects in women.⁹

Faster sprinters reached significantly lower velocities relative to v_{\max} at 20 m and 40 m and on average over the 0–20 m

and 20–40 m sections (Table 4). This is consistent with the difference found for τ because lower τ values indicate a greater ability to quickly reach a high percentage of v_{\max} . This is well supported by the literature; better sprinters accelerate for longer and so do not achieve the same relative velocities as their slower counterparts.^{7,35} Clark et al.¹⁵ reported relative velocities of $97.2\% \pm 0.9\%$ at 18.3 m in male NFL Combine athletes, which is considerably higher than the relative velocities reported in the present study at 20 m ($91.1\% \pm 1.2\%$). The athletes in the current study achieved higher v_{\max} values (11.37 ± 0.33 m/s vs. 9.08 ± 0.62 m/s) compared to the athletes in the study by Clark et al.¹⁵ Therefore, caution is advised when comparing τ values among studies of differing athletic populations. Differences in method-related factors, such as the sprint distance studied (e.g., 36.6 m vs. 80.0 m), will affect τ because shorter distances may not be sufficient for some athletes to reach

Table 5
Correlations between v_{\max} and 20-m split times.

	0–20 m (s)	20–40 m (s)	40–60 m (s)	60–80 m (s)	80–100 m (s)
v_{\max} (m/s)	-0.57** (-0.73 to -0.40)	-0.90** (-0.93 to -0.86)	-0.98** (-0.99 to -0.96)	-0.96** (-0.97 to -0.93)	-0.93** (-0.95 to -0.89)

Note: Results are presented as r (95%CI), with statistically significant correlations presented in boldface type.

** $p < 0.001$.

Abbreviation: CI, confidence interval.

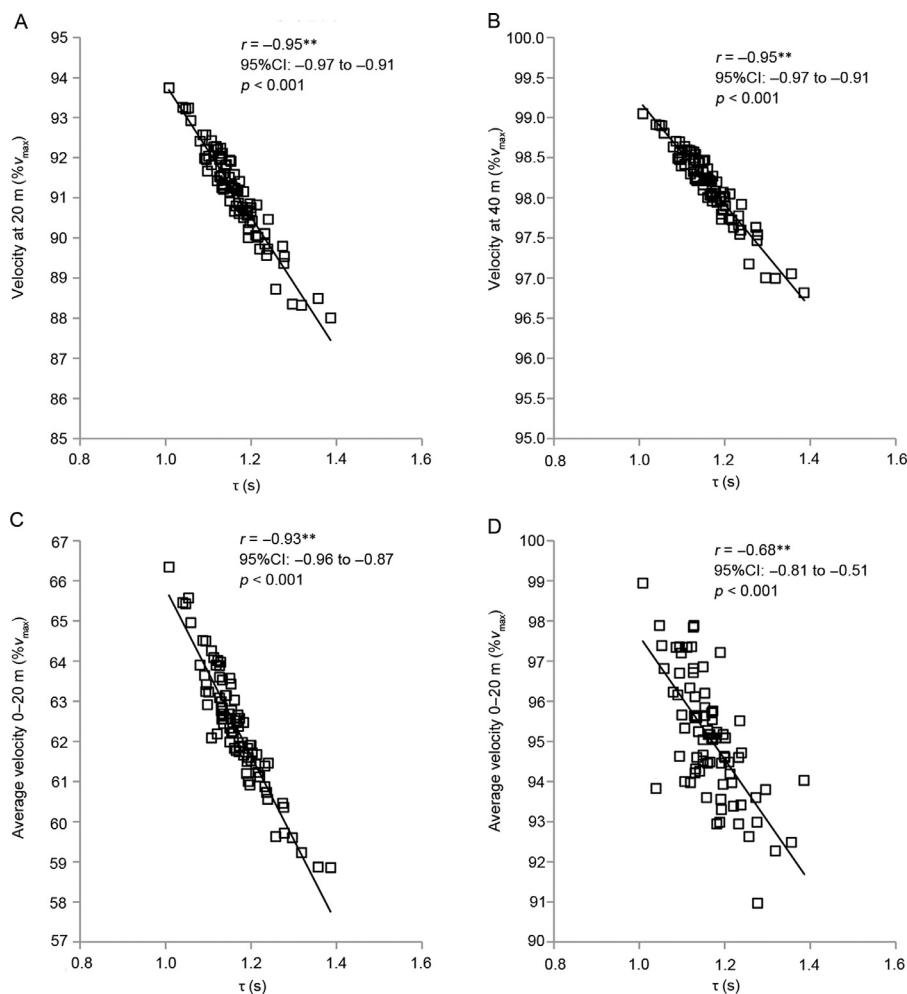


Fig. 2. Scatterplots illustrating the associations between τ , velocity at 20 m (A), velocity at 40 m (B), average velocity over 0–20 m (C), and average velocity over 20–40 m (D). $**p < 0.01$.

their true v_{\max} . This will result in the underestimation of that athlete's τ . Additionally, the start type (i.e., block start, standing start, 3-point start) will result in different values for initial acceleration, which will subsequently affect τ .

4.3. Relationships between sprint variables

The results shown in Table 5 highlight the critical importance of v_{\max} to each 20-m section of the 100-m sprint, with higher v_{\max} values associated with quicker sprint times. Stronger absolute correlations were found for the 20–40, 40–60, 60–80, and 80–100 m sections ($r \leq -0.90$), but a strong negative correlation was still found for the 0–20 m section ($r = -0.57$). This suggests that v_{\max} plays an important role in the initial acceleration phase, which is consistent with research on lower-level male sprinters (mean \pm SD 100 m personal best (PB): 11.17 ± 0.33 s) and athletes in field sports.^{7,15,36} In this study, the mean average 0–20 m velocity as a percentage of v_{\max} was 62.4%. A higher v_{\max} will, thus, lead to a higher average 0–20 m velocity in absolute units and, thus, quicker 20-m sprint times compared to an athlete with a lower v_{\max} .

The significant correlations presented in Fig. 2 indicate that as τ values increase, the percentage of v_{\max} achieved decreases. These findings confirm the accuracy of τ , estimated using the 4 split time approach, as an indicator of an athlete's relative acceleration ability. The relationship between τ and average velocity was lower for the 20–40 m section compared to the 0–20 m section ($r = -0.68$ vs. -0.93 , respectively), which suggests that τ is a better indicator of relative acceleration ability over the initial 20 m; however, the relationship is still large in the 20–40 m section.

Decreasing v_{\max} with no change in initial acceleration will lead to a decrease in τ and, thus, a greater relative acceleration ability; however, this change is entirely counterproductive and will lead to slower sprint times overall. Increasing maximal acceleration with no change in v_{\max} will lead to a decreased τ and, thus, improve an athlete's relative acceleration ability. This will subsequently enhance overall 100-m sprint performance because athletes will reach higher levels of their v_{\max} earlier. Consequently, we recommend any consideration of τ be made in conjunction with the athlete's v_{\max} . Sprint, technical, or strength-training methods are needed to develop maximal acceleration or methods that improve the athlete's

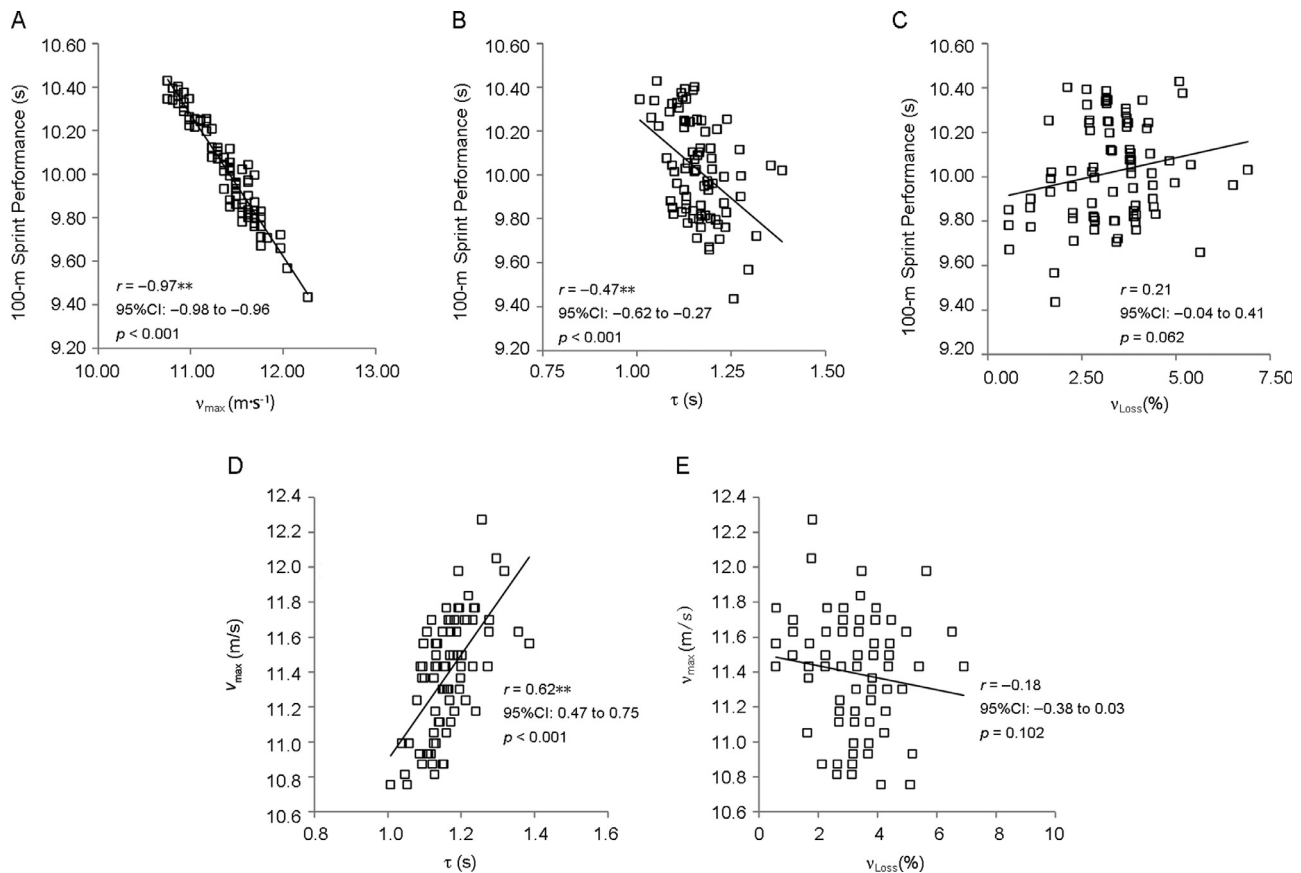


Fig. 3. Scatterplots illustrating the associations between 100-m sprint performance, v_{\max} , τ , and v_{Loss} (A–C) and the associations between v_{\max} , τ , and v_{Loss} (D–E). ** $p < 0.01$.

technical ability to apply force and, thereby, maintain a higher level of acceleration as a sprint progresses. Promising research using heavy-sled training by male amateur soccer players³⁷ has demonstrated improvements in maximal horizontal force, which logically imply improvements in maximal horizontal acceleration; however, such findings in an elite sprinter population have yet to be reported.

The results presented in Fig. 3 are consistent with other research and indicate a significant negative correlation between 100-m sprint performance time and v_{\max} .^{7,9,10} This can be explained by several factors relating to the phases of the 100-m sprint that have already been discussed. Briefly, sprinters with a higher v_{\max} will typically reach higher velocities during the acceleration phase and will take longer to reach v_{\max} . Subsequently, a longer acceleration and maximum velocity phase results in a shorter deceleration phase; thus, the decrease in sprint velocity as a result of fatigue is limited.^{7,9} Combined, these factors result in quicker overall 100-m sprint times.

This is the first study to assess the relationship between 100-m sprint performance, τ , and v_{Loss} in elite male sprinters. A moderate negative correlation was found for τ , which indicates that higher τ values were related to quicker sprint performance times. This is consistent with the findings of Volkov and Lapin,⁷ who found a large negative correlation ($r = -0.52$) between 100-m time and τ . In Volkov and Lapin's research, τ

was derived using a bi-exponential function that included the deceleration phase of a 100-m sprint in the model prediction. This negative relationship between τ and performance is counterintuitive because athletes with greater relative acceleration ability would be expected to be quicker over 100 m. However, this can be explained by the significantly large positive correlation found between v_{\max} and τ in the current study. Because higher τ values were associated with higher v_{\max} values, and higher v_{\max} values were associated with quicker 100-m sprint performance times, v_{\max} was, therefore, a confounding variable. By controlling for v_{\max} , a significant, very large positive correlation was found between τ and 100-m sprint performance, suggesting that for athletes with similar v_{\max} values, lower τ values were associated with quicker 100-m sprint performances, which is consistent with the conceptual understanding of τ .

No significant relationship was found between v_{\max} and v_{Loss} or between 100-m sprint performance and v_{Loss} , even when controlling for v_{\max} . The lack of a significant correlation between v_{\max} and v_{Loss} suggests that the ability to maintain maximal velocity is independent of an athlete's maximum speed capabilities. This ability, therefore, requires specific attention in training; however, future research is required to confirm this finding and to assess whether this is consistent in sprinters and team sport players of varying levels of ability.

The 100-m sprint is a multidimensional skill, and as the science underpinning the training and coaching of 100-m sprinters continues to improve, it is likely that success in major championships will require sprinters to excel in all factors assessed in the current study. They include short reaction times, high relative acceleration ability, high v_{\max} , and low v_{Loss} . Each individual athlete will likely have strengths and weaknesses in each of these variables, and they will manifest in terms of technical and physical deficiencies that should be examined in much more depth than has been undertaken in the current study. These weaknesses should be highlighted by sprint coaches and support staff and progressively targeted during an athlete's long-term development. Coaches are encouraged to use the methods outlined in the current study in conjunction with split times. Although 5 split times were used in the current study, additional splits (i.e., 10 m) would provide even greater information about a sprint; however, only 4 splits are required to model the acceleration phase accurately. Future research should continue to assess the effectiveness of interventions to improve key race variables in both male and female sprinters over a wide range of performance levels.

There were several limitations in the current study that must be acknowledged. First, wind speed was not factored into the current analysis. Although wind speed data were available for all performances (range: -0.8 m/s to 1.2 m/s), performances were not corrected because each 20-m section would have to be adjusted in order to complete the current analysis. This would require additional information (e.g., projected frontal area and coefficient of drag) that was not available. Second, because a field-based technique (i.e., the 4 split time modelling method) was used to derive some of the key variables used in this study (e.g., τ , velocity at 20 m, and velocity at 40 m), the accuracy of this method is dependent on the quality of the input data. Furthermore, the measurement method was not consistent across all data sources because a wide range of instruments was used, which is understandable, given the nature of the data set (i.e., 7 major events taking place between 1988 and 2017). All data were collected by experienced biomechanical teams and researchers, so it is likely that measurement errors were minimal and did not have any considerable effect on the results of the present study.

5. Conclusion

A 4 split time approach can model velocity-time and velocity-distance curves accurately during acceleration in elite male sprinters with 100-m sprint times ranging from 9.58 s to 10.59 s. Faster sprinters displayed higher v_{\max} and τ values than their slower counterparts. Maximum velocity had a strong negative correlation with the 0–20-m time and a near perfect negative correlation with all other 20-m sections and overall 100-m sprint performance time, highlighting the importance of v_{\max} to a 100-m sprinter. The variable τ is a useful indicator of a sprinter's relevant acceleration ability; a lower τ is associated with the ability to achieve a high percentage of v_{\max} , especially over the first 20 m. Furthermore, τ should be considered in conjunction only with v_{\max} because a lower τ is associated with a quicker 100-m sprint performance only after controlling

for v_{\max} . It is not recommended that τ values be compared among athletes unless identical procedures are used (e.g., sprint distance and starting protocol) because these factors will affect the resulting τ . Coaches and researchers are encouraged to utilize the current study's approach to assess key race variables that describe an athlete's performance capacities, which can subsequently be used to further inform training.

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Authors' contributions

RH conceived the study, compiled the data, performed the data analysis, interpreted the data, conducted statistical analyses, and drafted and revised the manuscript; ICK and AJH contributed to data interpretation and helped to draft and revise the manuscript. All authors have read and approved the final version of the manuscript, and agree with the order of presentation of the authors.

Competing interests

The authors declare that they have no competing interests.

Supplementary materials

Supplementary material associated with this article can be found in the online version at <https://doi.org/10.1016/j.jshs.2019.10.002>.

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