Examination of running pattern consistency across speeds

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**ABSTRACT**

Duty factor (DF) and step frequency (SF) are key running pattern determinants. However, running patterns may change with speed if DF and SF changes are inconsistent across speeds. We examined whether the relative positioning of runners was consistent: 1) across five running speeds (10–18 km/h) for four temporal variables [DF, SF, and their subcomponents: contact (\(t_c\)) and flight (\(t_f\)) time]; and 2) across these four temporal variables at these five speeds. Three-dimensional whole-body kinematics were acquired from 52 runners, and deviations from the median for each variable (normalised to minimum-maximum values) were extracted. Across speeds for all variables, correlations on the relative positioning of individuals were high to very high for 2–4 km/h speed differences, and moderate to high for 6–8 km/h differences. Across variables for all speeds, correlations were low between DF-SF, very high between DF-\(t_c\), and low to high between DF-\(t_f\), SF-\(t_c\), and SF-\(t_f\). Hence, the consistency in running patterns decreased as speed differences increased, suggesting that running patterns be assessed using a range of speeds. Consistency in running patterns at a given speed was low between DF and SF, corroborating suggestions that using both variables can encapsulate the full running pattern spectrum.

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**KEYWORDS**

Gait analysis; motion analysis; biomechanics; temporal variables; Relative positioning

**Introduction**

The spring–mass model represents running as a ‘bouncing’ gait modelled using a mass connected to a massless spring (Blickhan, 1989). In this model, the supporting leg behaves like a spring during stance and each stance is separated by a flight time (\(t_f\)), i.e., a period where the limbs are not in contact with the ground. The presence of this flight phase distinguishes running from walking (Novacheck, 1998).

Each runner adopts a unique and natural running pattern that is challenging to describe using a single variable (Folland et al., 2017). As early as 1985, the running pattern was viewed as a global system with several interconnected variables (Subotnick,
More recently, the synthetic review of van Oeveren et al. (2021) proposed that the full spectrum of running patterns could be described combining two temporal variables: step frequency (SF) and duty factor (DF), where DF reflects the relative contribution of the ground contact time \( t_c \) to the running stride (Folland et al., 2017; Minetti, 1998). According to van Oeveren et al. (2021), knowing DF and SF allows to categorise running patterns in one of five distinct categories, namely ‘stick’, ‘bounce’, ‘push’, ‘hop’, and ‘sit’, but keeping in mind that running patterns operate along a continuum. Individuals spontaneously and subconsciously adopt their own running pattern, a choice shown to be self-optimised and central in the development of an economical and safe running gait (Cavanagh & Williams, 1982; Moore et al., 2016; Moore, 2016; Williams & Cavanagh, 1987). The understanding of the individual running patterns might be important for improving performance, optimising training, and preventing running-related injuries.

The importance of DF and SF in determining running patterns (van Oeveren et al., 2021) corroborates previous findings. On the one hand, DF has been used to categorise runners with distinct running patterns (Lussiana et al., 2019; Patoz et al., 2020). Runners with a low DF exhibit a more symmetrical stance phase (similar brake and push times), anterior (midfoot and forefoot) strike pattern, and extended lower limb during \( t_c \) than runners with a high DF. In contrast, runners with a high DF exhibit greater lower limb flexion during \( t_c \), a more rearfoot strike pattern, and lesser work against gravity to generate forward propulsion (Lussiana et al., 2019; Patoz et al., 2020). Despite these biomechanical differences, the running economy of runners within these two DF groups are similar (Lussiana et al., 2019), suggesting two energetically equivalent strategies at endurance running speeds. On the other hand, SF can reveal individual muscle recruitment patterns of runners and strategies to increase running speed (Dorn et al., 2012) or achieve top-end running speeds (Salo et al., 2011). Even in subgroups of individuals with similar sprint velocities, a range of SF and step length combinations are present (Hunter et al., 2004).

Running speed affects DF and SF, with an increase in running speed decreasing DF (Lussiana et al., 2019; Minetti, 1998; van Oeveren et al., 2021) and increasing SF (Dorn et al., 2012; Ogueta-Alday et al., 2014; van Oeveren et al., 2021). These changes are likely related to changes in their subcomponent variables \( t_c \) and \( t_f \). Indeed, \( t_c \) decreases with an increase in running speed, whereas \( t_f \) increases (da Rosa et al., 2019; Lussiana et al., 2019; Ogueta-Alday et al., 2014; van Oeveren et al., 2021). Given the speed-dependency of these variables, van Oeveren et al. (2021) suggested using an absolute speed to define running patterns as stick, bounce, push, hop, and sit.

Worth noting is the large interindividual variations in temporal variables (DF, \( t_c \), \( t_f \), and SF) reported at absolute running speeds (Lussiana et al., 2019; Ogueta-Alday et al., 2014) and the large interindividual variations in the individual strategies adopted to adapt to changes in running speeds (Forrester & Townend, 2015; Hébert-Losier et al., 2015; Salo et al., 2011). For instance, a curve-clustering approach on the footstrike angle of runners across speeds revealed three subgroups: those that maintained a rearfoot strike pattern, those that maintained a forefoot or midfoot strike pattern, and those that transitioned from a rearfoot to a less rearfoot strike pattern with increasing speed (Forrester & Townend, 2015). Therefore, the running pattern of an individual could also change with speed if the relationship between or changes in the underlying temporal
variables are inconsistent across running speeds. Such understanding would then allow us assessing if the evaluation of running patterns could be generalised across speeds and studies.

Hence, our first aim was to assess if running patterns are consistent across running speeds by examining the consistency in four temporal variables (DF, SF, \( t_c \), and \( t_f \)). For instance, we investigated whether a runner with a high DF (with respect to the group median) at a slow running speed also exhibits a high DF at a faster running speed. We hypothesised that consistency would be greater when differences in running speeds were smaller, as previously observed for footstrike angle (Forrester & Townend, 2015).

Our second aim was to assess the consistency across the four temporal variables at an absolute running speed. Given that DF and SF are proposed to be two independent key running pattern determinants (van Oeveren et al., 2021), the association between these two variables should be low. Hence, we hypothesised that consistency would be low between DF and SF. On the other hand, we anticipated greater consistency between DF and its subcomponent variables (\( t_c \) and \( t_f \)) as well as between SF and \( t_c \) and \( t_f \).

Material and methods

Participants

Fifty-two runners, 32 men (age: \( 32 \pm 9 \) yr, mass: \( 66 \pm 11 \) kg, height: \( 175 \pm 7 \) cm, running distance: \( 53 \pm 21 \) km/week, running experience: \( 8 \pm 8 \) yr, and best half-marathon time: \( 92 \pm 10 \) min) and 20 women (age: \( 32 \pm 9 \) yr, mass: \( 52 \pm 6 \) kg, height: \( 162 \pm 4 \) cm, running distance: \( 50 \pm 22 \) km/week, running experience: \( 7 \pm 4 \) yr, and best half-marathon time: \( 102 \pm 12 \) min) participated in this study. For study inclusion, participants were required to be in good self-reported general health with no current or recent (<3 months) musculoskeletal injuries and to meet a certain level of running performance. More specifically, in the last year, runners were required to have competed in a road race with finishing times of \( \leq 50 \) min for 10 km or \( \leq 2 \) h for 21.1 km. The ethical committee of the National Sports Institute of Malaysia approved the study protocol prior to participant recruitment (ISNRP: 26/2015, which adhered to the latest version of the Declaration of Helsinki of the World Medical Association.

Experimental procedure

Each participant completed one experimental laboratory session. After providing written informed consent, participants ran 16 min (4 min at 9 km/h, 10 km/h, 12 km/h, and 14 km/h in that order) on a treadmill (h/p/cosmos mercury*, h/p/cosmos sports & medical gmbh, Nussdorf-Traunstein, Germany) as a warm-up ensuring stabilisation of shoe stiffness properties (Divert et al., 2005) and promoting treadmill familiarisation (Arnold et al., 2019; Lindorfer et al., 2020). Then, retro-reflective markers were positioned on individuals (described in Data Collection section) to assess running kinematics. For each participant, a 1-s static calibration trial was recorded, which was followed by \( 5 \times 30 \)-s runs at 10, 12, 14, 16, and 18 km/h (with 1-min recovery periods between each run) to collect three-dimensional (3D) kinematic data in the last 10-s segment of these runs.
(30 ± 2 running steps), resulting in at least 20 steps being analysed (Riazati et al., 2019). All participants were familiar with running on a treadmill as part of their usual training programs and wore their habitual running shoes during testing (shoe mass: 226 ± 37 g, stack height: 25 ± 3 mm, and heel-to-toe drop: 7 ± 3 mm).

Data collection

3D kinematic data were collected at 200 Hz using seven infrared Oqus cameras (five Oqus 300+, one Oqus 310+, and one Oqus 311+) and Qualisys Track Manager software version 2.1.1 build 2902 together with the Project Automation Framework Running package version 4.4 (Qualisys AB, Göteborg, Sweden). Thirty-five retro-reflective markers of 12 mm in diameter were used for static calibration and running trials, and were affixed to the skin and shoes of individuals over anatomical landmarks using double-sided tape following standard guidelines from the Project Automation Framework Running package (Tranberg et al., 2011) as already reported elsewhere (Lussiana et al., 2019). The 3D marker data were exported in .c3d format and processed in Visual3D Professional software version 5.02.25 (C-Motion Inc., Germantown, MD, USA). More explicitly, the 3D marker data were interpolated using a third-order polynomial least-square fit algorithm, allowing a maximum of 20 frames for gap filling, and subsequently low-pass filtered at 20 Hz using a fourth-order Butterworth filter.

Temporal variables

Running events were derived from the trajectories of the 3D marker data using similar procedures to those previously reported (Lussiana et al., 2019; Maiwald et al., 2009). More explicitly, a mid-foot landmark was generated midway between the heel and toe markers. Footstrike was defined as the instance when the mid-foot landmark reached a local minimal vertical velocity prior to it reaching a peak vertical velocity reflecting the start of swing. Toe-off was defined as the instance when the toe marker attained a peak vertical velocity before reaching a 7 cm vertical position. All events were verified to ensure correct identification and were manually adjusted when required.

\[ t_c \] was defined as the time from footstrike to toe-off of the same foot while \[ t_f \] was defined as the time from toe-off of one foot to footstrike of the contralateral foot. SF was calculated as \[ SF = 1/(t_c + t_f) \], and DF as \[ DF = t_c \cdot SF/2 \]. For all temporal variables, the values extracted from the 10-s data collection for each participant were averaged. To express the temporal variables as relative, each variable was normalised using the min-max scaler approach, i.e., \[ (x - x_{\text{min}})/(x_{\text{max}} - x_{\text{min}}) \] where \( x \) represents the value for a given participant and \( x_{\text{min/\text{max}}} \) the minimum/maximum among all participants at a given speed. The normalised variables were used in subsequent statistical analyses.

Statistical analysis

Descriptive statistics are presented using mean ± standard deviation. The consistency in running patterns across running speeds was evaluated by examining the relative positioning of runners for each temporal variable and tested speed. The relative positioning
was obtained by calculating the deviations from the median of the temporal values. These datasets were normally distributed based on Kolmogorov–Smirnov tests ($P \geq 0.34$). Pearson’s correlation coefficients ($r$) on the relative values together with corresponding 95% CI [lower, upper] and $P$-values were extracted to explore the consistency between each pair of running speeds for each of the four temporal variables. The same statistical approach was used to explore the consistency between each pair of temporal variables for each of the five running speeds. Correlations were considered very high, high, moderate, low, and negligible when absolute $r$ values were between 0.90 - 1.00, 0.70–0.89, 0.50–0.69, 0.30–0.49, and 0.00–0.29, respectively (Hinkle et al., 2002). Statistical analyses were performed using Jamovi (version 1.6, https://www.jamovi.org) with a level of significance set at $P \leq 0.05$ for all analyses.

**Results**

As speed increased from 10 to 18 km/h, DF and $t_c$ decreased by $8.5 \pm 2.8\%$ and $87 \pm 20$ ms, while $t_f$ and SF increased by $42 \pm 20$ ms and $0.42 \pm 0.16$ Hz, respectively (Table 1 and Figure 1). The relative DF, SF, $t_c$, and $t_f$ values for all participants and each running speed are depicted in Figure 2.

**Consistency across running speeds for each temporal variable**

Correlations for each one of the four relative temporal variables were high to very high for each pair of running speeds when changes were 2–4 km/h ($P < 0.001$, Table 2), except for the correlation between 10 and 14 km/h for $t_c$ being moderate. Correlations were moderate to high for each pair of running speeds when changes were 6–8 km/h for the four relative temporal variables ($P < 0.001$; Table 2).

The relative DF values for all participants and each running speed are depicted in Figure 3. According to the correlations reported in Table 2, similar figures and corresponding interpretations would result using the three other variables ($t_c$, $t_f$, and SF).

**Consistency across temporal variables for each running speed**

Correlations were low between relative DF and SF at all tested speeds ($P \leq 0.02$; Table 3). Correlations were very high between relative DF and $t_f$ at all tested speeds ($P < 0.001$); and high between relative DF and $t_c$ at 10 and 12 km/h ($P < 0.001$), but moderate at 14, 16, and 18 km/h ($P < 0.001$; Table 3).

<table>
<thead>
<tr>
<th>Running speed (km/h)</th>
<th>Duty factor (%)</th>
<th>Contact time (ms)</th>
<th>Flight time (ms)</th>
<th>Step frequency (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>38.6 ± 3.4</td>
<td>274 ± 24</td>
<td>81 ± 27</td>
<td>2.83 ± 0.16</td>
</tr>
<tr>
<td>12</td>
<td>35.1 ± 2.8</td>
<td>242 ± 19</td>
<td>103 ± 23</td>
<td>2.91 ± 0.18</td>
</tr>
<tr>
<td>14</td>
<td>33.2 ± 1.5</td>
<td>220 ± 18</td>
<td>112 ± 21</td>
<td>3.02 ± 0.19</td>
</tr>
<tr>
<td>16</td>
<td>31.2 ± 2.4</td>
<td>201 ± 17</td>
<td>121 ± 20</td>
<td>3.12 ± 0.21</td>
</tr>
<tr>
<td>18</td>
<td>30.1 ± 2.3</td>
<td>186 ± 15</td>
<td>124 ± 20</td>
<td>3.24 ± 0.24</td>
</tr>
</tbody>
</table>

Values are means ± standard deviations.

Table 1. Duty factor, contact time, flight time, and step frequency at five running speeds.
Figure 1. a) Duty factor (DF), b) step frequency (SF), c) contact time ($t_c$), and d) flight time ($t_f$) at five running speeds. Circles and error bars represent means and standard deviations, respectively.

Figure 2. Relative (deviations from the median) a) duty factor (DF), b) step frequency (SF), c) contact time ($t_c$), and d) flight time ($t_f$) values at five running speeds for all participants. Circles and error bars represent means and standard deviations, respectively. The combination of a colour and symbol represents a given participant and allows to observe the interindividual differences across both running speeds and temporal variables.
Table 2. Pearson’s correlation coefficients (r) and corresponding 95% confidence intervals [lower, upper] and P-values for the relationships of the relative values for pair of running speeds among five different speeds (10, 12, 14, 16, and 18 km/h) and for four temporal variables (duty factor, contact time, flight time, and step frequency).

<table>
<thead>
<tr>
<th>Running speed pair (km/h)</th>
<th>Statistics</th>
<th>Duty factor</th>
<th>Contact time</th>
<th>Flight time</th>
<th>Step frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>P</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 - 12</td>
<td>0.86 [0.76, 0.92]</td>
<td>&lt;0.001</td>
<td>0.83 [0.73, 0.90]</td>
<td>&lt;0.001</td>
<td>0.89 [0.81, 0.93]</td>
</tr>
<tr>
<td></td>
<td>0.98 [0.96, 0.99]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 - 14</td>
<td>0.72 [0.56, 0.83]</td>
<td>&lt;0.001</td>
<td>0.69 [0.51, 0.81]</td>
<td>&lt;0.001</td>
<td>0.78 [0.64, 0.87]</td>
</tr>
<tr>
<td></td>
<td>0.93 [0.88, 0.96]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>10 - 16</td>
<td>0.64 [0.45, 0.78]</td>
<td>&lt;0.001</td>
<td>0.63 [0.44, 0.77]</td>
<td>&lt;0.001</td>
<td>0.73 [0.56, 0.83]</td>
</tr>
<tr>
<td></td>
<td>0.86 [0.77, 0.92]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 - 18</td>
<td>0.58 [0.37, 0.74]</td>
<td>&lt;0.001</td>
<td>0.54 [0.32, 0.71]</td>
<td>&lt;0.001</td>
<td>0.66 [0.47, 0.79]</td>
</tr>
<tr>
<td></td>
<td>0.77 [0.63, 0.86]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>12 - 14</td>
<td>0.91 [0.84, 0.95]</td>
<td>&lt;0.001</td>
<td>0.90 [0.83, 0.94]</td>
<td>&lt;0.001</td>
<td>0.93 [0.88, 0.96]</td>
</tr>
<tr>
<td></td>
<td>0.97 [0.94, 0.98]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 - 16</td>
<td>0.79 [0.66, 0.88]</td>
<td>&lt;0.001</td>
<td>0.83 [0.72, 0.90]</td>
<td>&lt;0.001</td>
<td>0.83 [0.73, 0.90]</td>
</tr>
<tr>
<td></td>
<td>0.92 [0.87, 0.96]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 - 18</td>
<td>0.68 [0.51, 0.81]</td>
<td>&lt;0.001</td>
<td>0.71 [0.54, 0.82]</td>
<td>&lt;0.001</td>
<td>0.73 [0.57, 0.84]</td>
</tr>
<tr>
<td></td>
<td>0.83 [0.71, 0.90]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14 - 16</td>
<td>0.86 [0.77, 0.92]</td>
<td>&lt;0.001</td>
<td>0.90 [0.83, 0.94]</td>
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</tr>
<tr>
<td></td>
<td>0.97 [0.95, 0.98]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14 - 18</td>
<td>0.73 [0.57, 0.83]</td>
<td>&lt;0.001</td>
<td>0.82 [0.70, 0.89]</td>
<td>&lt;0.001</td>
<td>0.77 [0.63, 0.86]</td>
</tr>
<tr>
<td></td>
<td>0.88 [0.80, 0.93]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16 - 18</td>
<td>0.86 [0.77, 0.92]</td>
<td>&lt;0.001</td>
<td>0.91 [0.85, 0.95]</td>
<td>&lt;0.001</td>
<td>0.90 [0.83, 0.94]</td>
</tr>
<tr>
<td></td>
<td>0.93 [0.88, 0.96]</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Statistically significant correlations (P ≤ 0.05) are in bold font. Correlations were considered very high, high, moderate, low, and negligible when absolute r values were between 0.90–1.00, 0.70–0.89, 0.50–0.69, 0.30–0.49, and 0.00–0.29, respectively (Hinkle et al., 2002). Cells were coloured according to the intensity of the correlations, i.e., the larger the correlation, the darker the shaded area.

Correlations between relative SF and t_f were moderate at all speeds (P < 0.001), except for being high at 18 km/h (P < 0.001). Correlations were low between relative SF and t_c at 10, 12, and 14 km/h (P ≤ 0.03), and moderate at 16 and 18 km/h (P < 0.001; Table 3).

Correlations between relative t_c and t_f were moderate at 10 km/h (P < 0.001), low at 12, 14, and 16 km/h (P ≤ 0.04). Correlations were negligible at 18 km/h (P = 0.21; Table 3)

The relative temporal variables are depicted in Figure 4 for all participants running at 10 km/h. According to the correlations reported in Table 3, similar figures and corresponding interpretations would result using the four other running speeds (12, 14, 16, and 18 km/h).

**Discussion and implications**

In agreement with our first hypothesis, smaller differences between two running speeds were associated with greater consistency in running patterns, i.e., greater consistency in the four temporal variables examined (DF, SF, t_c, and t_f). Correlations of the relative values were high to very high for 2–4 km/h speed differences, whereas moderate to high for 6–8 km/h differences. In agreement with our second hypothesis, the consistency between DF and SF variables was low at each tested speed, and greater between DF
and both its subcomponents as well as between SF and both its subcomponents than between DF and SF variables. Across speeds, correlations were low between relative DF and SF, very high between relative DF and $t_f$, and low to high between relative DF and $t_c$, SF and $t_f$, and SF and $t_f$. From a practical perspective, the lower consistency in running patterns observed as speed differences increased suggests that running patterns should be
assessed at a range of speeds or at a specific speed. In other words, the generalisation of running patterns across speeds may not be valid. Noteworthy is the considerable inter-individual differences observed in terms of the evolution of the relative variables with changes in speed, with some runners demonstrating similar running patterns across speeds and others changing running patterns. The low consistency between DF and SF at a given running speed corroborates previous findings that SF does not necessarily encapsulate the same running pattern information than DF. As proposed by van Oeveren et al. (2021), the full spectrum of running patterns can be described using both DF and SF. Individuals spontaneously and subconsciously adopt their own running pattern. This spontaneous choice was shown to be self-optimised, which is a central element in the development of an economical and safe running gait (Cavanagh & Williams, 1982; Moore et al., 2016; Moore, 2016; Williams & Cavanagh, 1987). Hence, being able to analyse the full spectrum of running patterns may be important to interpret measurements, to design and test specific coaching interventions, and to conduct research to answer questions regarding performance, running economy, and injury risk.

The stronger correlations of the relative temporal variables (DF, SF, \( t_c \), and \( t_f \)) for 2–4 km/h than 6–8 km/h speed differences (Table 2) indicate greater consistency in variables when changes in running speeds are smaller. In other words, the running pattern is less consistent when measured over a larger speed range (Figures 2 and 3). This result supports that the running pattern should be defined at a given speed (van Oeveren et al., 2021). Moreover, large interindividual variations in the consistency in running patterns across running speeds were observed (Figure 3). For instance, there were runners with a DF higher than the median at 10 km/h, but a decreasing DF with increasing speed resulting in a DF closer to the median at 18 km/h; runners with a DF higher than the median at all tested speeds; runners with a DF lower than the median at 10 km/h, but an increasing DF with increasing speed resulting in a DF closer to the median at 18 km/h; and runners with a DF much lower than the median at all tested

<table>
<thead>
<tr>
<th>Variable pair</th>
<th>Statistics</th>
<th>10 km/h</th>
<th>12 km/h</th>
<th>14 km/h</th>
<th>16 km/h</th>
<th>18 km/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>DF – SF</td>
<td>( r )</td>
<td>0.38 [0.11, 0.59]</td>
<td>0.38 [0.13, 0.60]</td>
<td>0.34 [0.07, 0.56]</td>
<td>0.32 [0.05, 0.55]</td>
<td>0.41 [0.16, 0.62]</td>
</tr>
<tr>
<td></td>
<td>( P )</td>
<td>0.006</td>
<td>0.005</td>
<td>0.01</td>
<td>0.02</td>
<td>0.002</td>
</tr>
<tr>
<td>DF – ( t_f )</td>
<td>( r )</td>
<td>-0.98 [-0.99, -0.97]</td>
<td>-0.96 [-0.98, -0.93]</td>
<td>-0.94 [-0.96, -0.89]</td>
<td>-0.91 [-0.95, -0.85]</td>
<td>-0.91 [-0.95, -0.85]</td>
</tr>
<tr>
<td></td>
<td>( P )</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>DF – ( t_c )</td>
<td>( r )</td>
<td>0.77 [0.63, 0.86]</td>
<td>0.71 [0.54, 0.82]</td>
<td>0.67 [0.48, 0.80]</td>
<td>0.65 [0.46, 0.79]</td>
<td>0.57 [0.35, 0.73]</td>
</tr>
<tr>
<td></td>
<td>( P )</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>SF – ( t_f )</td>
<td>( r )</td>
<td>-0.53 [-0.70, -0.30]</td>
<td>-0.62 [-0.76, -0.41]</td>
<td>-0.64 [-0.78, -0.44]</td>
<td>-0.67 [-0.80, -0.49]</td>
<td>-0.74 [-0.85, -0.59]</td>
</tr>
<tr>
<td></td>
<td>( P )</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>SF – ( t_c )</td>
<td>( r )</td>
<td>-0.30 [-0.53, -0.03]</td>
<td>-0.38 [-0.59, -0.12]</td>
<td>-0.47 [-0.66, -0.23]</td>
<td>-0.50 [-0.68, -0.27]</td>
<td>-0.51 [-0.69, -0.28]</td>
</tr>
<tr>
<td></td>
<td>( P )</td>
<td>0.03</td>
<td>0.006</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>( t_c ) – ( t_f )</td>
<td>( r )</td>
<td>-0.65 [-0.79, -0.46]</td>
<td>-0.49 [-0.67, -0.25]</td>
<td>-0.37 [-0.58, -0.11]</td>
<td>-0.29 [-0.52, -0.02]</td>
<td>-0.18 [-0.43, 0.10]</td>
</tr>
<tr>
<td></td>
<td>( P )</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>0.007</td>
<td>0.04</td>
<td>0.21</td>
</tr>
</tbody>
</table>

Statistically significant correlations \( P \leq 0.05 \) are in bold font. Correlations were considered very high, high, moderate, low, and negligible when absolute values were between 0.90–1.00, 0.70–0.89, 0.50–0.69, 0.30–0.49, and 0.00–0.29, respectively (Hinkle et al., 2002). Cells were coloured according to the intensity of the correlations, i.e., the closer to one the correlation, the darker the red shaded area and the closer to minus one the correlation, the darker the blue shaded area.
speeds. This agrees with previous observations that individuals adapt to running speeds differently (Forrester & Townend, 2015; Hébert-Losier et al., 2015; Salo et al., 2011), which might be linked to differences in anthropometric characteristics, age, and running training (van Oeveren et al., 2019). Performing a more detailed analysis that incorporates clustering approaches might reveal subgroups that respond similarly to changes in running speeds. As absolute running speeds were used rather than relative speeds (based on the level of participants), it would not be possible to identify whether sudden changes in DF and/or SF take place at given relative intensities. Overall, coaches should evaluate the running pattern of their athletes using a range of speeds or at a specific speed.

As indicates the low correlations between relative DF and SF values at all tested speeds (Table 3), the consistency between these two variables was low. Similarly, Figure 4 depicts how runners with a low/high DF can present with either a low/high SF. These results again reflect previous ones wherein SF does not necessarily encapsulate the same running pattern information than DF, and that combining DF and SF information should allow to describe the full running pattern spectrum (van Oeveren et al., 2021). As depicted in Figure 4, each of the five categories proposed by van Oeveren et al. (2021) were represented herein. Specifically, there were stick (high DF and median SF), bounce (low DF and median SF), hop (high SF and median DF), push (low SF and median DF), and sit (median DF and SF) runners. Moreover, there were runners in between these categories, which also confirms that running patterns operate along a spectrum (Figure 4) (van Oeveren et al., 2021).

Given that the risk of injury was shown greater in runners with a lower DF, especially in softer shoes (Malisoux et al., 2022), quantifying DF might be informative for lower-limb injury prevention. The present study found very high correlations between relative DF and \( t_f \) values at all tested speed (Table 3 and Figure 4), suggesting that the relative \( t_f \) is equivalent to the relative DF. In other words, individual variations in \( t_f \) are equivalent to variations in DF. The interrelatedness of DF and \( t_f \) and their importance in running are
further highlighted by their established correlations to ground reaction force metrics. Indeed, DF and $t_f$ are related to the average vertical ground reaction force during $t_f$ (Beck et al., 2020) and effective vertical impulse during $t_f$ (Dorn et al., 2012), respectively. Both the average vertical ground reaction force during $t_f$ and effective vertical impulse during $t_f$ are proportional to the peak vertical ground reaction force, as supports the sine wave model of the vertical ground reaction force (Morin et al., 2005) and experimental data (Bonnaerens et al., 2021). The present study reported lower association between relative $t_c$ and DF values (correlations were moderate to high; Table 3 and Figure 4) than relative $t_c$ to DF values. This result is primarily driven by the midrange DF runners (Figure 4). Altogether, these observations indicate that runners with a relatively long $t_f$ (or short $t_c$) are runners with a relatively low DF within a group of runners, i.e., DF is mainly controlled by $t_f$ and less by $t_c$. Overall, the kinematic differences previously observed between high and low DF runners (Lussiana et al., 2019; Patoz et al., 2020) should generalise well to runners with short and long $t_f$, but might not generalise as well to runners with long and short $t_c$. Among these three variables (DF, $t_c$, and $t_f$), one might be easier to evaluate subjectively, which would be ideal for track and field running coaches, athletes, and practitioners seeking to describe running patterns along a spectrum. Indeed, running coaches could then subjectively evaluate their runners and identify the low DF runners using either DF, $t_f$, or $t_c$. Nevertheless, further studies comparing subjective and objective evaluations of runners using DF, $t_f$, and $t_c$ would be needed to assess if one of these variables is easier to subjectively evaluate than the others.

The moderate to high correlations between relative SF and $t_f$ values and low to moderate correlations between relative SF and $t_c$ values (Table 3 and Figure 4) follow the same trend than those between relative DF and $t_f$ or $t_c$, i.e., correlations were larger with $t_f$ than with $t_c$. Hence, $t_f$ also determines more of the variation of SF than $t_c$.

Bear in mind that the running trials were performed on a treadmill, hence generalisation to overground running is not guaranteed (Bailey et al., 2017). Nevertheless, as temporal variables between treadmill and overground running are largely comparable (Van Hooren et al., 2020), our results may still apply to overground running. In addition, absolute running speeds were used, which enables generalisability with findings from other studies using absolute speeds. However, future studies might seek to examine the consistency in running patterns based on DF and SF variables across relative speeds [i.e., percent of maximal aerobic speed or maximal oxygen uptake, or percent of maximal lactate steady state to avoid influencing motor unit recruitment strategy (Burnley & Jones, 2018; Fletcher et al., 2009)] to establish whether sudden changes in DF and/or SF could take place at given relative intensities. Moreover, the eligibility criteria about the level of running performance was independent of the sex of the runners, implying that women were of a higher relative standard than men. Furthermore, no sex distinction was considered in the present study. Although a relatively large sample size was employed ($n = 52$), which would have allowed us to separate out men ($n = 32$) and women ($n = 20$), we preferred to not do such separation to increase the statistical power as well as to keep the method as simple as possible to have an easy-to-read manuscript. Besides, even though correlations are known to be affected by the range of the sample (a large range could lead to very high
correlations), the present study reported only a $13 \pm 12\%$ larger range for men than women when considering the four temporal variables at all tested speeds. The larger range reported for men than women could not be explained by the difference in relative performance standard between men and women. Indeed, even though women reported a $10\%$ slower best half-marathon racing time than men, their range of best racing time was $20\%$ larger than men, which is opposed to the $10\%$ smaller range obtained for the temporal variables compared to men. Nevertheless, future work should focus on the impact of sex when examining the running pattern consistency across running speeds.

**Conclusion**

This study revealed that the consistency in running patterns decreased as speed differences increased. Therefore, running patterns should be assessed using a range of speeds or at a specific speed. Moreover, there were large interindividual differences across the relative temporal variables examined ($DF$, $SF$, $t_c$, and $t_f$), highlighting individualised strategies to adapt in running speed changes. In accordance with a previously proposed running pattern model, relative $DF$ and $SF$ were weakly related, indicating that both variables encapsulate different information on running patterns.

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**Authors’ contribution**

TL carried out the lab work and collected data; AP and BB performed the data analysis, carried out the statistical analysis, and wrote the original draft of the manuscript; AP, TL, BB, CG, DM, and KH-L critically revised the manuscript; TL, CG, DM, and KH-L conceived of the study, designed the study, and coordinated the study. All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

**Data availability statement**

The datasets supporting this article are available on request to the corresponding author.

**Disclosure statement**

The authors declare no conflicts of interest.

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