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Self-paced treadmill speed differentially affects gait variability and stability in walking and running☆

Cagla Kettner *, Michael Herzog, Thorsten Stein

BioMotion Center, Institute of Sports and Sports Science, Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany

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ABSTRACT

Self-paced treadmills allow individuals to continuously regulate belt speed and may more closely replicate overground locomotion than fixed-speed conditions. However, their effects on gait variability and stability, particularly during running, remain incompletely understood. This study compared self-paced (SFP) and constant-speed (CON) treadmill locomotion during walking and running at matched average speeds. Twenty-eight healthy adults completed SFP and CON walking and running trials. Spatiotemporal characteristics were assessed using mean values and coefficients of variation (CV) for stride length, step frequency, step width, and stance ratio (duty factor in running). Global stability was evaluated using detrended fluctuation analysis (DFA), and local dynamic stability using the maximum Lyapunov exponent. During walking, SFP slightly increased stride length ($p = 0.004$) and reduced stance ratio ($p = 0.025$), while step width and step frequency were unchanged. CV increased for stride length ($p < 0.001$), step frequency ($p < 0.001$), and stance ratio ($p < 0.001$), whereas step width variability remained unchanged. DFA scaling exponent was increased during SFP walking ($p < 0.001$). Local dynamic stability decreased in the thigh ($p < 0.001$) and foot ($p < 0.001$). In running, no significant differences were observed between SFP and CON for mean spatiotemporal variables, their variability, or global stability. Local dynamic stability improved in the trunk ($p = 0.036$), shank ($p < 0.001$), and foot ($p = 0.002$). These findings demonstrate gait-mode-specific responses to self-paced treadmill speed regulation. Walking appears more sensitive to externally imposed speed constraints, whereas running preserves its spatiotemporal characteristics and dynamical organization.

1. Introduction

Human locomotion is a fundamental motor behavior supporting independence and daily participation. Treadmills are widely used to investigate walking and running under controlled laboratory conditions because they allow precise speed regulation and extended data collection (Sloot et al., 2014). Traditionally, treadmill research has relied on constant-speed operation, which enhances repeatability but constrains natural stride-to-stride speed fluctuations (Dingwell et al., 2001; Fukuchi et al., 2019). Compared to self-selected overground locomotion, constant-speed treadmill walking has been shown to alter gait variability and nonlinear stability characteristics, suggesting that external speed constraints influence the dynamical structure of gait (Dingwell et al., 2001; Terrier & Dériaz, 2011).

To address these limitations, self-paced treadmill systems have been developed that allow individuals to regulate speed more similarly to overground locomotion through feedback-controlled belt adjustments (Sloot et al., 2014). Self-paced modes permit spontaneous speed modulation but remain influenced by controller dynamics (e.g., belt acceleration limits) and environmental constraints (Plotnik et al., 2015; Qian et al., 2020; Song et al., 2020). Studies comparing self-paced and constant-speed treadmill walking report similar mean spatiotemporal outcomes when average speed is matched, but greater variability under self-paced conditions (Sloot et al., 2014; Theunissen et al., 2022). However, direct comparisons during running remain limited. Investigating running is relevant because walking and running differ fundamentally in their control demands and biomechanics (Novacheck, 1998). Unlike walking, running includes a flight phase, has shorter ground-contact times, and is commonly modeled as a spring-mass system in which elastic energy storage and return play an important role (Blickhan, 1989; Ferris et al., 1998; Novacheck, 1998). These gait-mode-specific demands may influence how belt-speed adaptations affect

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* Corresponding author.
E-mail addresses: cagla.kettner@kit.edu (C. Kettner), michael.herzog@kit.edu (M. Herzog), thorsten.stein@kit.edu (T. Stein).

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stride-to-stride fluctuations and dynamic stability. Therefore, investigating both walking and running is important to determine whether the effects of self-paced treadmill control are gait-mode-specific.

Beyond mean spatiotemporal measures, gait stability provides important insight into locomotor control under different treadmill modes (Dingwell et al., 2001; Kao & Pierro, 2021; Qian et al., 2020). Gait stability can be assessed using complementary approaches that quantify stability at different analytical levels (Riva et al., 2014; Winter et al., 2024). One important distinction is between global and local stability. Global stability reflects the longer-timescale organization of gait fluctuations and can be assessed using detrended fluctuation analysis (DFA) (Hausdorff et al., 1996). The scaling exponent (DFA-α) quantifies the temporal correlation structure of stride-to-stride fluctuations. Values close to 0.5 indicate uncorrelated fluctuations, whereas values between 0.5 and 1 indicate persistent long-range correlations. Values above 1, however, may reflect nonstationary Brownian-like dynamics rather than physiological long-range power-law correlations (Hausdorff et al., 1996, 1997; Phinyomark et al., 2020). In contrast, local dynamic stability reflects the sensitivity of gait to small perturbations and is commonly quantified using the maximum Lyapunov exponent (MLE) on kinematic time series, where larger values indicate faster divergence of kinematic trajectories and reduced local stability (Dingwell et al., 2001). In addition to these nonlinear stability measures, spatiotemporal variability, often quantified using the coefficient of variation (CoV), is frequently reported in gait research (Godin et al., 2024; Riva et al., 2014). In this context, variability refers to the magnitude of stride-to-stride fluctuations (Stergiou & Decker, 2011). Variability-based metrics have been interpreted as indirect indicators of stability (Hamacher et al., 2011). However, increased variability does not necessarily indicate reduced stability and may instead reflect functional adaptability (Stergiou & Decker, 2011; van Emmerik et al., 2016). Therefore, stability-related outcomes derived from variability measures should be interpreted cautiously and considered alongside complementary nonlinear analyses.

Previous research has shown that treadmill walking can modify both local dynamic stability and gait organization, indicating that experimental constraints may alter the dynamical structure of gait even when mean spatiotemporal parameters remain similar (Dingwell et al., 2001; Rohafza et al., 2022). However, it remains unclear to what extent self-paced versus constant-speed treadmill modes systematically influence spatiotemporal variability as well as global and local stability, particularly during running. Therefore, this study investigated the effects of self-paced compared with constant-speed treadmill mode on spatiotemporal variability and gait stability during walking and running. Spatiotemporal means and variability were used to quantify differences in gait patterns, while stability was assessed using complementary nonlinear methods (DFA for global and MLE for local stability). It was hypothesized that, first, self-paced mode would not substantially alter mean spatiotemporal parameters but would increase their variability compared with constant-speed locomotion (Sloot et al., 2014). Second, self-paced mode was expected to increase DFA-α within the range of 0.5 to 1, reflecting stronger long-range correlations in stride-to-stride fluctuations and greater DFA-based global stability. This expectation was based on the assumption that removing the external speed constraint imposed by constant-speed treadmill locomotion would allow stride interval fluctuations to exhibit a more spontaneous fractal structure with power-law long-range correlations. Third, self-paced mode was hypothesized to decrease local dynamic stability in the lower limbs, hip, and trunk, indicated by larger MLE values, as continuous belt-speed adaptations may introduce small repeated perturbations at the foot-belt interface (Kao & Pierro, 2021; Qian et al., 2020). Finally, because walking and running differ fundamentally in their control demands and biomechanics, the effects of self-paced treadmill control on spatiotemporal variability, DFA-based global stability, and MLE-based local dynamic stability were expected to be gait-mode-specific.

2. Methods

2.1. Participants

An *a priori* power analysis was conducted for a paired-samples *t*-test comparing self-paced and constant-speed conditions, based on previously reported effects for step width (Theunissen et al., 2022). The expected paired-samples effect size was calculated from the reported means and standard deviations. Because the within-participant correlation between conditions was not reported in the article, it was obtained from Theunissen et al. ($r = 0.92$), resulting in an effect size of $dz = 0.58$. Assuming a desired statistical power of 0.90, and an alpha level of 0.05 (one-tailed), the required sample size was calculated to be $n = 27$ participants using G*Power (Version 3.1.9.7). To allow for a balanced crossover design with equal ordering of constant-speed (CON) and self-paced conditions (SFP), 28 participants were recruited (14 females; age: 25.2 ± 2.1 years; height: 1.75 ± 0.10 m; body mass: 73.2 ± 12.2 kg). Participants had no known neurological or musculoskeletal disorders affecting gait and provided written informed consent prior to testing. The sample primarily consisted of sports science students who regularly participated in practical sport activities involving running components, such as track and field, football, and basketball. All participants reported being familiar with treadmill running. The study was approved by the ethics committee of the Karlsruhe Institute of Technology.

2.2. Study design

An overview of the study protocol is provided in Fig. 1. The session began with a 10-min warm-up and familiarization period on a split-belt treadmill (M−Gait, Motek Medical, Amsterdam, The Netherlands), which is consistent with previous treadmill walking and running protocols and exceeds the approximately 6–7 min reported to achieve stable treadmill running kinematics in healthy adults (Lavcanska et al., 2005; Meyer et al., 2019). During SFP trials, belt speed was continuously adjusted using the Motek self-paced feedback-control algorithm implemented in D-Flow. The algorithm uses the subject's anterior-posterior position on the treadmill, estimated from the average position of four pelvic markers, as an approximation of center of mass position. At activation, a reference position is stored, and treadmill speed is continuously adjusted relative to this position. Speed increases when the participant moves anterior to the reference position and decreases when the participant moves posterior to it. For SFP walking, participants were instructed to walk at their usual everyday walking pace. The resulting mean speed was then used to set the matched CON walking trial. For SFP running, participants were instructed to select a comfortable running pace that they could maintain for approximately 20 min. The resulting mean speed was then used to set the matched CON running trial. Walking trials (4 min) were then performed in SFP and CON conditions in counterbalanced order. Running trials (2:45 min) followed in counterbalanced order, separated by 2 min of rest. After the running trials, perceived exertion was assessed using the Borg Rating of Perceived Exertion scale (RPE, 6–20; Borg, 1982). Participants were asked, "How hard was the exercise for you?" and ratings below 12 were used to confirm that perceived exertion remained low (Kettner et al., 2026). Participants wore an overhead safety harness during all trials.

2.3. Data acquisition and preprocessing

Three-dimensional whole-body kinematic data were captured using a 16-camera motion capture system (Vicon Motion Systems, Oxford, UK, 200 Hz). Ground reaction forces were collected simultaneously from the force plates embedded in the treadmill (1000 Hz). A total of 49 retro-reflective markers were positioned on predefined anatomical landmarks of the head, trunk, pelvis, and both upper and lower limbs (Fig. 2). Marker trajectories were reconstructed in Vicon Nexus (V2.16) and further processed in MATLAB (R2024a; MathWorks Inc., Natick, MA,

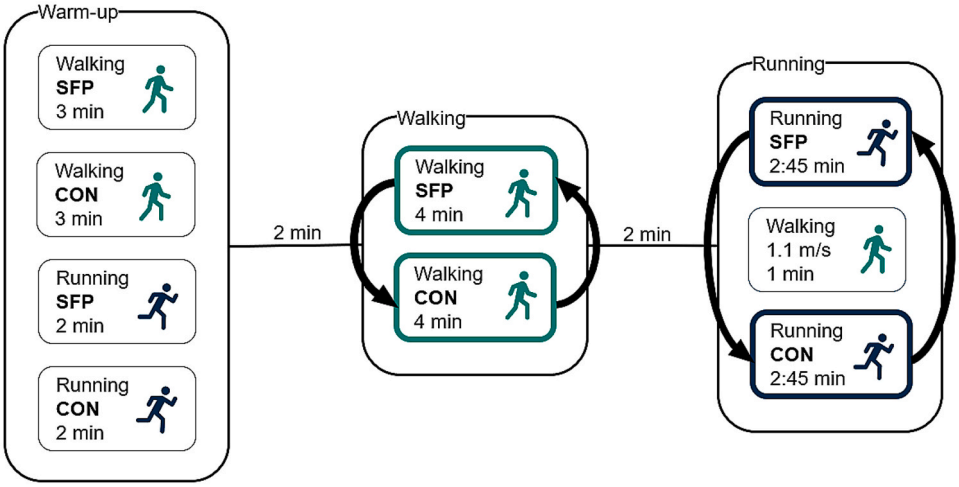

Fig. 1. Schematic overview of the experimental protocol.

USA). Kinematic and force data were filtered using fourth-order low-pass Butterworth filters with cutoff frequencies of 10 and 20 Hz, respectively.

2.4. Data analysis

Gait speed. Walking and running speed were determined from treadmill belt speed outputs in D-Flow (Motek Medical, Amsterdam, The Netherlands). Belt speed was averaged across each trial to obtain a condition-specific mean. These values were used to verify successful speed matching between the CON and SFP conditions.

Spatiotemporal and variability characteristics. For both walking and running conditions, 150 consecutive strides per condition were included in the analysis. Strides were defined based on gait events of both legs, which were also used to determine stance phase duration. During walking, initial contact and toe-off were identified from sagittal-plane kinematic data using a marker-based method. Initial contact was defined as maximal forward heel displacement relative to the pelvis, and toe-off as maximal backward toe displacement (Zeni et al., 2008). This method was used because force-plate-based event detection from the split-belt treadmill was not reliable for all walking steps. Participants occasionally crossed the treadmill midline or placed a foot partially on the contralateral belt, which made side-specific force-based detection unreliable during double-support phases. For steps with clearly assignable foot placement, marker-based and force-based gait events were compared and showed good agreement with differences mostly within 1–3 frames, corresponding to 5–15 ms. For running, gait events were determined from vertical ground reaction force data. Initial contact was defined as the instant when vertical force exceeded 20 N, and toe-off when it fell below 20 N (Fellin et al., 2010; Jiang et al., 2024). All automatically detected gait events were visually inspected using stick-figure visualizations to ensure accuracy. From 150 strides, stride length, step frequency, and step width were calculated. For walking, stance ratio (proportion of stride time in stance) was calculated. For running, the same variable was reported as duty factor, consistent with running literature (Van Hooren et al., 2020). For each participant and condition, mean values and CoV were computed.

Global stability. Long-range temporal correlations in stride time were quantified using DFA (Hausdorff et al., 1996). For this analysis, 178 strides during walking and 193 strides during running were included, representing the maximum number of consecutive strides available across participants and conditions. The stride time series was centered by subtracting its mean and transformed into a cumulative sum signal (Eq. (1)). The integrated signal was segmented into non-overlapping windows ranging from $\Delta n = 4$ to 60 data points. This window range followed recommendations for short time series (128–256 strides) (Phinyomark et al., 2020). Within each window, a second-order polynomial trend was removed to account for low-frequency components. The root-mean-square fluctuation of the detrended signal was calculated for each window size (Eq. (2); Bryce & Sprague, 2012).

$$A(w) = \sum_{i=1}^{w} (x(i) - x_{avg}) \tag{1}$$

$$F(\Delta n) = \sqrt{\frac{1}{N} \sum_{w=1}^{N} \left(A(w) - A_{\Delta n}(w)\right)^2} \tag{2}$$

If scale-invariant dynamics are present, F(Δn) increases with window size according to a power-law relationship that appears linear on logarithmic axes (Eq. (3)). The slope of this log–log relationship (DFA-α) represents the strength of temporal correlations in the stride time series. In terms of gait pattern, anti-persistent fluctuations (DFA-$\alpha < 0.5$) indicate that a longer-than-average stride time is more likely to be followed by a shorter-than-average stride time, and vice versa, reflecting alternating step-to-step corrections. Persistent fluctuations ($0.5 <$ DFA-$\alpha < 1$) indicate that stride-time deviations tend to persist across subsequent strides; for example, shorter-than-average stride times tend to be followed by shorter-than-average stride times, and longer-than-average stride times by longer-than-average stride times (Hausdorff et al., 1997; Jordan et al., 2007).

$$F(\Delta n) \propto (\Delta n)^{DFA-\alpha} \tag{3}$$

Local stability. Local dynamic stability was evaluated for the trunk, hip, thigh, shank, and foot using the MLE derived from vertical marker cluster data (Fig. 2; three to four markers per segment; Ekizos et al., 2018; Jordan et al., 2009; Santuz et al., 2018). The vertical component was selected because it provides a consistently cyclic signal for state-space reconstruction and may be less directly affected by anterior-posterior belt regulation and changes in position within the treadmill workspace than anterior-posterior or mediolateral marker trajectories. Such effects may introduce nonstationarity into the time series, which can affect MLE estimates. As in the global stability analysis, 178 strides during walking and 193 strides during running were included. The complete stride time series was time-normalized to 100 samples per stride, resulting in continuous time series of 17,800 data points for walking and 19,300 data points for running for the MLE analysis (Raffalt et al., 2019). State-space reconstruction parameters were determined separately for walking and running for each segment. The embedding

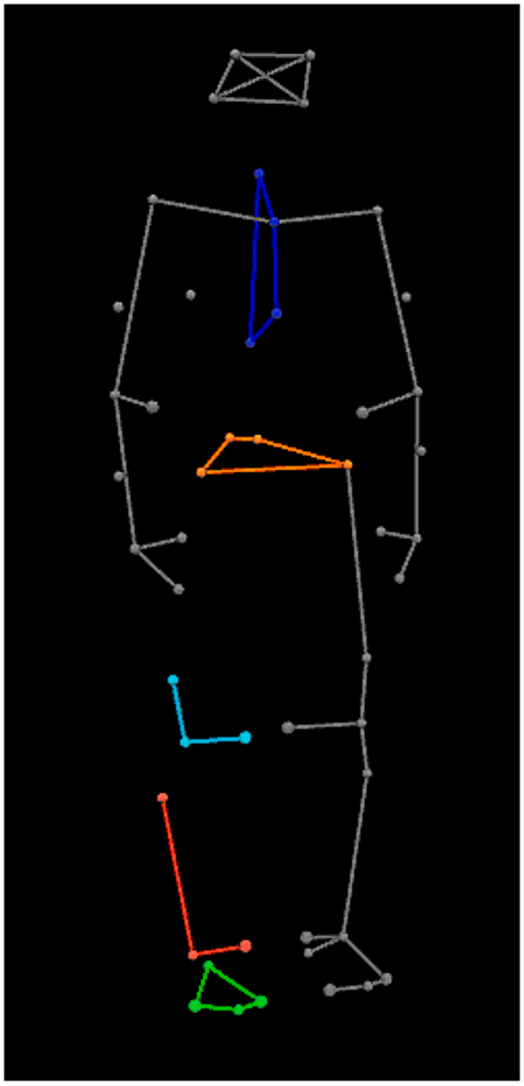

Fig. 2. Schematic representation of the right-sided body segments and their corresponding reflective marker clusters included in the local dynamic stability analysis: trunk (blue), hip (orange), thigh (cyan), shank (red), and foot (green). Both left and right sides were analyzed; however, only the right side is shown for simplicity. Grey markers indicate the remaining markers of the full-body marker set that were not included in the stability analysis.

dimension (m) was estimated using the false nearest neighbor method, and the time delay (τ) was identified from the first local minimum of the average mutual information function. Because m and τ can influence MLE estimates, the same reconstruction parameters were applied across SFP and CON within each participant, locomotion mode, and segment. Specifically, the maximum m and the median τ across trials were used for each participant, locomotion mode, and segment (Hoenig et al., 2019). The resulting m and τ values are reported in Table 1. After state-space reconstruction, nearest neighboring trajectories were identified and the average logarithmic divergence curve was calculated using Rosenstein's algorithm (Eq. (4); Rosenstein et al., 1993). The short-term divergence exponent (λ) was calculated as the slope of the average logarithmic divergence curve over 0–0.5 stride cycles, and the same fitting region was used for all participants, segments, locomotion modes, and conditions. This exponent quantified local dynamic stability, with lower λ indicating greater stability. An example of the reconstructed state space and the fitted portion of the divergence curve is provided in Supplementary Fig. 1.

Table 1
State-space reconstruction parameters used for maximum Lyapunov exponent analysis. Mean embedding dimension (m) and time delay (τ) values are reported separately for walking and running for each segment. τ represents the time delay in normalized samples.

Walking		
	m	***τ***
λ_{trunk}	9	34
λ_{hip}	8	35
λ_{thigh}	10	26
λ_{shank}	10	40
λ_{foot}	10	30
Running		
	m	***τ***
λ_{trunk}	10	26
λ_{hip}	9	24
λ_{thigh}	9	22
λ_{shank}	10	36
λ_{foot}	10	27

$$S(t) = [z(t), z(t+\tau), \cdots, z(t+(m-1)\tau)] \quad (4)$$

2.5. Statistics

Statistical analyses were conducted using SPSS (Version 29.0; IBM Corp., Armonk, NY, USA). Analyzed variables included mean gait speed; mean values and CoV of stride length, step frequency, step width, and stance ratio (duty factor during running); as well as DFA-α and λ for the trunk, hip, thigh, shank, and foot. For stride length, stance ratio (duty factor during running), and λ of the thigh, shank, and foot, both legs were analyzed separately. Both left- and right-leg data were processed. Because separate analyses showed consistent SFP–CON condition effects across limbs, and because limb asymmetry was not a focus of the present study, only right-leg data are presented to avoid redundant reporting. Normality was assessed using the Kolmogorov-Smirnov test. Differences between CON and SFP were assessed using one-sided paired-samples t-tests or Wilcoxon signed-rank tests when normality assumptions were violated. For gait speed, a two-sided paired-samples t-test was applied due to the absence of a directional hypothesis. Effect sizes (Cohen's d) were interpreted as small ($\leq$0.50), medium (0.50–0.80), or large ($\geq$0.80) (Cohen, 1988). The level of statistical significance was set at $\alpha = 0.05$.

3. Results

3.1. Gait speed

Two participants were excluded from the walking analyses because the difference in mean walking speed between SFP and CON exceeded 0.10 m/s. This threshold was applied to ensure adequate speed matching between treadmill modes and to minimize the influence of residual speed differences on speed-sensitive spatiotemporal and nonlinear stability outcomes (Fukuchi et al., 2019; Jordan et al., 2009). For the remaining 26 participants, walking speed did not differ between CON (1.40 ± 0.18 m/s) and SFP (1.42 ± 0.19 m/s) ($p = 0.054$). For running, speed matching was successful for all 28 participants. Running speed did not differ between CON (2.39 ± 0.30 m/s) and SFP (2.38 ± 0.32 m/s) ($p = 0.267$). Individual speeds and percentage differences between SFP and CON are reported in Supplementary Tables 1 and 2 for walking and running, respectively.

3.2. Spatiotemporal characteristics

All spatiotemporal results are presented in Table 2.

Table 2
Mean values and coefficients of variation (CoV) of stride length, step frequency, step width, and stance ratio (duty factor during running) for walking and running under constant-speed (CON) and self-paced (SFP) conditions. Descriptive statistics are presented as mean ± standard deviation. Statistically significant results are indicated in bold. # indicates that a Wilcoxon signed-rank test was applied due to non-normal data distribution.

Walking				
	CON	**SFP**	**p**	**Cohen's d**
Mean stride length (m)	1.51 ± 0.12	1.54 ± 0.13	**0.004**	−0.57
Mean step frequency (Hz)	1.88 ± 0.14	1.89 ± 0.15	0.112	−0.24
Mean step width (m)	0.12 ± 0.03	0.12 ± 0.02	0.417	0.04
Mean stance ratio (%)	60.38 ± 1.19	60.21 ± 1.06	**0.025**	**0.40**
CoV stride length (%)	1.39 ± 0.65	2.36 ± 1.30	**< 0.001**#	**−0.96**
CoV step frequency (%)	1.70 ± 0.79	2.05 ± 0.88	**< 0.001**#	**−0.77**
CoV step width (%)	17.52 ± 5.39	17.42 ± 5.20	0.415	0.04
CoV stance ratio (%)	0.81 ± 0.17	0.92 ± 0.23	**<0.001**#	**−1.27**
Running				
	CON	**SFP**	**p**	**Cohen's d**
Mean stride length (m)	1.85 ± 0.24	1.85 ± 0.24	0.450	−0.02
Mean step frequency (Hz)	2.58 ± 0.15	2.58 ± 0.14	0.423	−0.04
Mean step width (m)	0.10 ± 0.03	0.10 ± 0.03	0.097	−0.25
Mean duty factor (%)	38.26 ± 3.96	38.27 ± 3.72	0.491	−0.04
CoV stride length (%)	3.83 ± 1.94	4.19 ± 1.43	0.295#	−0.16
CoV step frequency (%)	2.03 ± 0.32	2.24 ± 0.61	0.145#	−0.37
CoV step width (%)	22.88 ± 11.76	22.22 ± 10.68	0.699#	0.15
CoV duty factor (%)	3.08 ± 1.30	3.70 ± 2.05	0.116#	−0.30

During walking, stride length was greater in SFP than CON ($p = 0.004$), and stance ratio was lower ($p = 0.025$). Step frequency and step width did not differ between conditions.

Spatiotemporal variability was higher in SFP for all parameters except step width (stride length: $p < 0.001$; step frequency: $p < 0.001$; stance ratio: $p < 0.001$).

During running, neither mean values nor variability differed between SFP and CON.

3.3. Global stability

DFA-α values for walking and running are shown in Table 3. During walking, DFA-α was higher for SFP compared with CON ($p < 0.001$), indicating more persistent and less random stride-to-stride fluctuations (Fig. 3a). In CON, six participants showed DFA-α values below 0.5, one participant showed DFA-α above 1, and the remaining 19 participants showed values between 0.5 and 1. In SFP, no participant showed DFA-α values below 0.5, nine participants showed DFA-α values above 1, and the remaining 17 participants showed values between 0.5 and 1.

For running, DFA-α values were likewise within the persistent range (0.5–1) for all participants but did not differ significantly between the CON and SFP conditions (Fig. 3b).

3.4. Local stability

Local dynamic stability (λ) results are presented in Table 3. During walking, λ was higher in SFP for the thigh ($p < 0.001$) and foot ($p < 0.001$), indicating reduced local dynamic stability at these segments.

During running, λ was lower in SFP for the trunk ($p = 0.036$), shank ($p < 0.001$), and foot ($p = 0.002$), indicating greater local dynamic stability.

Table 3
Global stability (DFA-α) and local dynamic stability (λ) during walking and running under constant-speed (CON) and self-paced (SFP) conditions. Values are presented as mean ± standard deviation. Statistically significant differences are shown in bold.

Walking				
	CON	**SFP**	**p**	**Cohen's d**
DFA-α	0.61 ± 0.14	0.87 ± 0.20	**< 0.001**	**−1.24**
λ_{trunk}	0.82 ± 0.07	0.80 ± 0.08	0.105	0.25
λ_{hip}	0.89 ± 0.06	0.89 ± 0.09	0.415	−0.04
λ_{thigh}	0.92 ± 0.08	0.97 ± 0.08	**< 0.001**	**−0.75**
λ_{shank}	0.71 ± 0.09	0.72 ± 0.10	0.131	−0.23
λ_{foot}	0.86 ± 0.10	0.92 ± 0.13	**< 0.001**	**−0.69**
Running				
	CON	**SFP**	**p**	**Cohen's d**
DFA-α	0.67 ± 0.09	0.70 ± 0.10	0.113	−0.23
λ_{trunk}	1.09 ± 0.09	1.06 ± 0.09	**0.036**	**0.35**
λ_{hip}	1.31 ± 0.12	1.29 ± 0.13	0.125	0.22
λ_{thigh}	1.07 ± 0.14	1.05 ± 0.10	0.177	0.18
λ_{shank}	0.78 ± 0.07	0.73 ± 0.09	**< 0.001**	**0.81**
λ_{foot}	1.11 ± 0.13	1.06 ± 0.15	**0.002**	**0.58**

4. Discussion

This study aimed to understand how self-paced treadmill locomotion differs in spatiotemporal characteristics, global stability, and local dynamic stability during walking and running compared with constant-speed conditions. During walking, self-paced mode led to slightly longer strides and a reduced stance ratio, while step width and step frequency remained unchanged. In line with the first hypothesis, variability of stride length, stance ratio, and step frequency increased under self-paced conditions. In contrast, no significant differences in spatiotemporal parameters or their variability were detected during running. Regarding global stability, as assessed through DFA-based stride-time dynamics, self-paced walking showed higher DFA-α values, indicating stronger long-range temporal correlations in stride-to-stride fluctuations, whereas running did not show significant differences between conditions. For local dynamic stability, walking partially supported the hypothesis, with increased MLE values in the thigh and foot, while other segments remained unchanged. In running, the trunk, shank, and foot showed improved local dynamic stability, contrary to the third hypothesis.

4.1. Self-paced treadmill control increases spatiotemporal variability in walking but not in running

For walking, self-paced mode led to only small changes in mean spatiotemporal parameters, with stride length increasing by ~ 3 cm and stance ratio decreasing by ~ 0.2%. Because walking speed is determined by the combination of stride length and step frequency, a small stride length difference can occur despite similar mean speeds between conditions. These findings are in line with previous speed-matched comparisons reporting minor changes in average gait measures (Sloot et al., 2014; Theunissen et al., 2022). In contrast to the small changes in mean values, spatiotemporal variability increased for stride length, stance ratio, and step frequency. This likely reflects the removal of the constant belt-speed constraint. Constant-speed treadmills act as an external pacemaker that limits natural speed fluctuations, whereas self-paced systems allow self-regulation of forward progression (Sloot et al., 2014; Wiens et al., 2019).

The unchanged step width variability is consistent with previous findings showing that speed fluctuations during self-paced walking

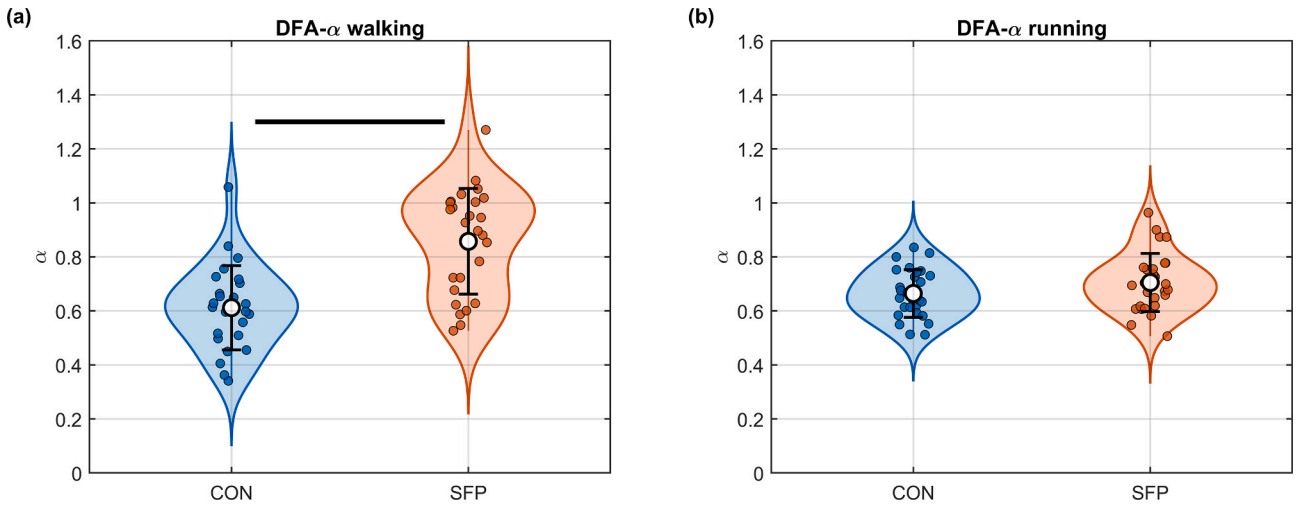

Fig. 3. Violin plots showing DFA-α values representing global stability during (a) walking and (b) running in constant-speed (CON) and self-paced (SFP) conditions. A horizontal black line indicates a statistically significant difference between CON and SFP.

primarily increase step length variability rather than lateral adjustments (Castano & Huang, 2021; Sloot et al., 2014). Since belt speed changes mainly affect forward progression, adaptations occur predominantly through modulation of step length and step frequency. In contrast, mediolateral foot placement is closely linked to balance regulation and is actively controlled to maintain stability (Bauby & Kuo, 2000; Bruijn & Van Dieën, 2018), which may explain why step width variability remained unaffected.

During running, neither mean spatiotemporal parameters nor their variability differed between conditions. This different response compared to walking may reflect fundamental differences in gait organization. Walking is often described by an inverted pendulum model, in which the center of mass vaults over a relatively stiff stance leg (Kuo, 2007). This gait pattern requires continuous step-to-step regulation to maintain dynamic stability (Lacquaniti et al., 2012). Running, in contrast, is characterized by faster and more rhythmically constrained dynamics and is commonly described by a spring-mass model, in which the center of mass oscillates over a compliant leg in a cyclic manner (Blickhan, 1989; Margaria, 1976; Seyfarth et al., 2002). This mechanically organized pattern may contribute to a rhythmic structure that is less influenced by treadmill control mode.

4.2. Global stability: Self-paced control increases long-range correlations in walking but not in running

Greater scaling exponents reflect more persistent stride-interval fluctuations and reduced stride-to-stride corrective regulation when values remain within the physiological long-range correlation range of 0.5–1 (Hausdorff et al., 1996; Jordan et al., 2009). During walking, DFA-α increased under self-paced conditions, indicating stronger long-range temporal correlations in stride-time fluctuations. Rather than indicating reduced stability per se, this finding suggests that self-paced treadmill control allowed a more persistent stride-to-stride temporal structure, whereas constant-speed treadmill walking may have constrained these correlations. Externally imposed rhythmic constraints, such as metronome-paced walking, reduce persistence and increase step-to-step regulation (Hausdorff et al., 1996; Terrier et al., 2005). Constant-speed treadmill walking imposes a comparable constraint, requiring continuous positional adjustments (Rohafza et al., 2022; Wiens et al., 2019). When speed can be regulated continuously in self-paced mode, fewer corrections may be required, resulting in more persistent stride dynamics.

The individual DFA-α values support this interpretation but also warrant caution. During CON, six participants showed DFA-α values below 0.5, indicating anti-persistent stride-time fluctuations. From a biomechanical perspective, this means that a longer-than-average stride time was more likely to be followed by a shorter-than-average stride time, and vice versa, suggesting alternating stride-to-stride adjustments around the fixed belt speed. No participant showed this pattern during SFP. However, nine participants showed DFA-α values above 1 during SFP compared with one participant during CON. Because DFA-α values above 1 exceed the range typically interpreted as stationary persistent long-range correlations, these findings should not be interpreted simply as greater DFA-based global stability. Rather, they indicate that the stride-time series during SFP had a different temporal structure, potentially including slow-varying or nonstationary components (Hausdorff et al., 1996, 1997; Phinyomark et al., 2020).

In running, global stability did not differ between conditions, suggesting that stride fluctuation organization remains largely unaffected by speed regulation. Running exhibits cyclic spring-mass dynamics (Blickhan, 1989), which may reduce the need for continuous step-to-step adjustments and contribute to consistent fluctuation structure across speeds. Consistent with this interpretation, previous studies have shown that the scaling properties of running are less affected by speed changes (Jordan et al., 2009), and remain relatively consistent when runners adjust their step frequency to imposed metronome frequencies (Agresta et al., 2019).

4.3. Local dynamic stability shows gait-mode-specific responses to self-paced control

The MLE results should be interpreted separately from the DFA findings because the two analyses quantify different aspects of gait dynamics. DFA-α characterizes the temporal organization of stride-time fluctuations (Hausdorff et al., 1996, 1997), whereas MLE quantifies the sensitivity of segmental kinematic trajectories to small perturbations (Dingwell et al., 2001). Regarding the third hypothesis, walking results partially supported reduced local dynamic stability under self-paced conditions. Increased MLE values, therefore reduced local dynamic stability, were observed in the thigh and foot, whereas the hip, trunk, and shank remained unchanged.

In self-paced mode, continuous belt-speed adjustments may act as small, repeated perturbations at the foot-belt interface, challenging the locomotor control system and reducing local dynamic stability compared with constant-speed walking (Kao & Pierro, 2021; Qian et al., 2020). These subtle variations likely require repeated adjustments, particularly in distal segments directly involved in ground contact, which may explain why decreased local stability was observed primarily

in the thigh and foot. The absence of changes in the hip and trunk suggests that these local effects were segment-specific, possibly reflecting the different functional roles of distal segments in adapting to minor gait speed variations during walking.

In running, local dynamic stability did not decrease under self-paced conditions and was slightly improved in some segments, contrary to the third hypothesis. Running is characterized by cyclic spring-mass dynamics, in which elastic energy is stored and released within the muscle–tendon system while the center of mass follows a bouncing trajectory (Blickhan, 1989). This mechanically organized movement pattern may attenuate the influence of small speed variations on segmental dynamics, as minor speed changes can be accommodated within the inherent loading–unloading cycle. Moreover, running involves shorter stance times and higher step frequencies compared with walking (Novacheck, 1998), leaving limited time for feedback-based adjustments within each step. Consequently, control during running relies more strongly on intrinsic mechanical behavior and feedforward mechanisms (Geyer et al., 2006; Lacquaniti et al., 2012). Together, these mechanisms may explain why local dynamic stability was maintained or slightly enhanced during self-paced running.

4.4. Limitations

Several limitations should be considered when interpreting the present findings. First, identical controller parameters were used for walking and running, which may have influenced belt-speed fluctuations differently across gait modes (Castano & Huang, 2021). Second, although speed matching was statistically successful, small residual differences in speed may have influenced nonlinear stability measures, which are sensitive to gait speed (Jordan et al., 2009). Third, the estimation of DFA and MLE was based on time series comprising 178 and 193 strides for walking and running, respectively. Although prior research indicates that nonlinear stability measures can be obtained with datasets of similar length (Bruijn et al., 2009; Phinyomark et al., 2020), the reliability and precision of these estimates generally improve with longer recordings. Fourth, local dynamic stability was calculated from vertical marker-cluster trajectories only. Although this provided a consistent cyclic input signal for segment-level comparisons, it does not capture the full multidirectional dynamics of locomotion, including anterior-posterior braking-propulsion dynamics or mediolateral balance control. Fifth, different gait-event detection methods were used for walking and running. Walking events were identified using a marker-based method, whereas running events were detected from vertical ground reaction forces, because split-belt force data were not consistently suitable for side-specific event detection during walking. However, this methodological difference does not affect the primary comparisons between SFP and CON. Sixth, treadmill locomotion differs from overground locomotion, limiting direct generalization (Dingwell et al., 2001; Semaan et al., 2022). Finally, running speed (~8.6 km/h) was at the lower end of typical running speeds, and findings may differ at higher velocities (Van Oeveren et al., 2021).

5. Conclusion

Self-paced treadmill walking increased spatiotemporal variability and altered global stability, as reflected by stronger long-range temporal correlations in stride-to-stride fluctuations. Local dynamic stability, reflecting the sensitivity of segmental kinematic trajectories to small perturbations, decreased in the thigh and foot during walking. In contrast, running showed no significant differences in spatiotemporal characteristics or global stability, and local stability was enhanced in the trunk, shank and foot. These findings indicate that walking is more sensitive to externally imposed speed constraints, whereas running preserves its dynamical organization. Overall, the effects of self-paced treadmill control appear to be gait-mode-specific.

CRediT authorship contribution statement

Cagla Kettner: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Michael Herzog:** Writing – review & editing, Data curation. **Thorsten Stein:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Ethics approval and consent to participate

All experiments were approved by the Karlsruhe Institute of Technology Ethics Committee. All participants provided written and informed consent to participate.

Consent for publication

All participants provided written and informed consent for the publication of these data.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability: Data for this study are available from the corresponding author on reasonable request.

Appendix A. Supplementary data

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