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Running gait produces long range correlations: A systematic review

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ABSTRACT

Background: Walking and running are common forms of locomotion, both of which exhibit variability over many gait cycles. Many studies have investigated the patterns generated from that ebb and flow, and a large proportion suggests human gait exhibits *Long Range Correlations* (LRCs). LRCs refer to the observation that healthy gait characteristic, like stride times, are positively correlated to themselves over time. Literature on LRCs in walking gait is well known but less attention has been given to LRCs in running gait.
Research question: What is the state of the art concerning LRCs in running gait?
Methods: We conducted a systematic review to identify the typical LRC patterns present in human running gait, in addition to disease, injury, and running surface effects on LRCs. Inclusion criteria were human subjects, running related experiments, computed LRCs, and experimental design. Exclusion criteria were studies on animals, non-humans, walking only, non-running, non-LRC analysis, and non-experiments.
Results: The initial search returned 536 articles. After review and deliberation, our review included 26 articles. Almost every article produced strong evidence for LRCs apparent in running gait and in all running surfaces. Additionally, LRCs tended to decrease due to fatigue, past injury, increased load carriage and seem to be lowest at preferred running speed on a treadmill. No studies investigated disease effects on LRCs in running gait.
Significance: LRCs seem to increase with deviations away from preferred running speed. Previously injured runners produced decreased LRCs compared to non-injured runners. LRCs also tended to decrease due to an increase in fatigue rate, which has been associated with increased injury rate. Lastly, there is a need for research on the typical LRCs in an overground environment, for which the typical LRCs found in a treadmill environment may or may not transfer.

1. Introduction

Walking and running are ubiquitous forms of human locomotion. People naturally adjust their walking and running patterns to meet ever-changing task demands and adapt to new environmental constraints [1]. *Gait variability* refers to the changes in gait characteristics that occur from one step to the next [2] such as timing differences that occur across gait cycles. Gait variability can be defined in terms of its magnitude (i.e., standard deviation) and its structure (i.e., patterns expressed over time) [1]. Those properties depend on many sources of influence such as a person's state of learning [1,3,4], the task at-hand [1,4,5], and/or environmental constraints [1,4].

Variability in walking has been studied extensively in healthy populations and in many clinically relevant settings, revealing many important distinctions [1,2,6–17]. Typically, the magnitude of variability increases with disease progression and aging, where older adults and those with neurodegenerative diseases tend to have a larger magnitude of variability than younger persons and diseased individuals tend to have a larger magnitude of variability than healthy individuals [1,2,10,18]. Furthermore, the structure of variability, as described in more detail below, is more complex and somewhat predictable for healthy and younger individuals but less complex in older or diseased individuals [1,10,19]. Moreover, relative to young, healthy counterparts, those individuals produce variability that tends towards becoming both overly determined and unpredictable, depending on the context. The overwhelming majority of research has investigated gait variability from the perspective of walking with fewer studies examining variability in running gait [6,8,9,11,14,15,20–22]. Thus, a more complete investigation is needed to determine the similarities in walking and running gait variability, particularly in terms of a property known as long range correlations.

Long Range Correlations (LRCs) characterize the degree to which movements are related from one moment to the next. The presence of LRCs signifies that the timing from one step would be positively

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correlated with step timing from many steps earlier. That is, the variability of a person's steps in the past could have dramatic effects on the variability of current and future steps when walking or running. The most common method to measure LRCs in human movement science is *Detrended Fluctuation Analysis* (DFA) [23]. In short, DFA provides an output variable alpha (α), where $0.5 < \alpha \leq 1$ is mathematically indicative of LRCs, although other ranges have been suggested based on empirical observations in human gait and positive bias in the DFA algorithm [5,10,23–26]. Other methods to measure LRCs in human movement science that are included in this review include the *Fractal Dimension* (FD) of a curve, *Higuchi's Fractal Dimension* (HFD), or *Rescaled Range Analysis* (R/S). The FD of a curve depicts LRCs when $1 < \text{FD} < 2$ [27]. Similarly, LRCs are apparent when $1 < \text{HFD} < 2$, where $\text{HFD} \to 1$ is indicative of weaker LRCs and $\text{HFD} \to 2$ is indicative of stronger LRCs [28]. Further, R/S produces the *Hurst* (H) exponent, which is equivalent to α for measuring LRCs, where $0.5 < \text{H} \leq 1$ is indicative of a persistent time series, hence LRCs [29,30]. Measuring LRCs in human performance variables is important because LRCs have been proposed as a sign of healthy physiological systems [31–33] as proposed in the *Optimal Movement Variability Hypothesis* (OMVH) [3,34].

The OMVH suggests that variability in mature motor skills strikes a balance between complexity and predictability [34–36]. Human gait entails coordination of many underlying physiological interactions, in addition to task and environmental constraints. Complexity in human movements – the richness of one's behavioral repertoire – are thought to reflect one's ability to adapt to novel circumstances while coordinating those influences. Predictability refers to the consistency in movement patterns such as the consistency of spatiotemporal features of gait. On the one hand, healthy human movements require a balance between those properties, maintaining patterns appropriate for a given context while remaining flexible to draw on one's repertoire to meet changes in context. On the other hand, OMVH suggests that unhealthy human movements deviate from optimality in two ways. First, when a system's predictability is high and complexity is low, this reflects a reduced flexibility to adapt to environmental perturbations (green time series in Fig. 1, where α is not defined) [19,34]. Second, if the system's predictability and complexity are both low, movement will exhibit less regulated behavior (α closer to 0.5, blue structure in Fig. 1) [19,34]. Both situations make the system less adaptable to perturbations and are directly related to an increased presence of disease and/or the natural aging process [14,19,33,37–39]. The OMVH proposes that skilled and coordinated action, like walking, should strike a balance between the extremes implied in Fig. 1 [34]. LRCs fit within the OMVH because they represent the multiple interactions of a system within the body [31,37,40] and indicate an optimal state of motor performance [33,40,41]. In this review, we draw upon the OMVH as a theoretical framework with which to interpret LRCs that may be present in running gait, given its proven utility in interpreting gait dynamics observed during walking [4,41,42].

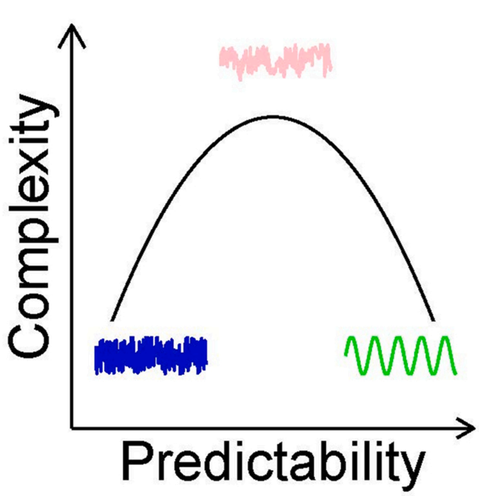

Fig. 1. Optimal movement variability hypothesis. Less than optimal could be too random and unstable (blue) or too predictable and rigid (green). An optimal structure (pink) indicates higher adaptive ability.

As mentioned above, LRCs have been studied extensively in walking gait. Past literature has reported that normal walking gait, without perturbations, exhibit LRCs [9,11,22,43–45], with some articles indicating LRCs in slow, preferred, and fast paced walking [8,15]. Persons with neurodegenerative diseases, like Parkinson's and Huntington's disease, show a decrease in their LRCs compared to healthy subjects when walking [43,44], in line with the OMVH. Additionally, LRCs tend to decrease naturally as we age [14,44]. LRCs of the system are detectable through walking gait parameters, but similar dynamics may be detectable in other forms of locomotion.

Although LRCs have been studied considerably in walking gait, fewer experiments have examined LRCs while running. In those cases, a cursory review of the literature implies inconsistent findings concerning the nature of LRCs in running gait. One study [16] looked at the stability and time dependent structure of gait in walking compared to running on a treadmill, as well as the transition between walking and running and vice versa. When comparing walking and running stride intervals, the LRCs were more apparent when measured from the ankle during walking (walking $\alpha \sim 0.78$, running $\alpha \sim 0.75$), while LRCs were more apparent when measured at the head during running (walking $\alpha \sim 0.76$, running $\alpha \sim 0.80$). Those results could suggest that different body segments produce different LRC patterns. Alternatively, those patterns could imply conflicting evidence about the differences in LRCs between walking and running. Such potential contradictions suggest a need to aggregate the extant literature regarding LRCs comparing running and walking. To that end, we conducted a systematic review to investigate the effects that running has on LRCs and the consequent implications for human health, performance, and rehabilitation. Our aim was to identify the typical LRC patterns for human running gait, the differential effects that running and walking have on LRCs, the effects of injury and disease on running gait LRCs, and the effect that surface has on the LRCs in running gait.

2. Methods

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were followed for this systematic review [46]. PubMed, IEEExplore, Scopus and Web of Science were used from August 2020 to December 2022 using the following Boolean string:

("fractal" OR "multifractal" OR "complexity" OR "long range correlation" OR "long range dependence" OR "serial dependence" OR "self-similar*" OR "detrended fluctuation analysis" OR "rescaled range analysis" OR "power spectral density" OR "pink noise") AND ("running" OR "run" OR "sprint" OR "sprinting" OR "jog" OR "jogging") AND ("gait" OR "stride" OR "treadmill").

Due to the limitation of search characters in the Scopus engine in 2020, the Boolean string had to be split into three separate, smaller strings to include all articles, as follows:

1. ("fractal" OR "multifractal" OR "complexity" OR "long range correlation") AND ("running" OR "run" OR "sprint" OR "sprinting" OR "jog" OR "jogging") AND ("gait" OR "stride" OR "treadmill")
2. ("long range dependence" OR "serial dependence" OR "self-similar*" OR "detrended fluctuation analysis") AND ("running" OR "run" OR "sprint" OR "sprinting" OR "jog" OR "jogging") AND ("gait" OR "stride" OR "treadmill")
3. ("rescaled range analysis" OR "power spectral density" OR "pink noise") AND ("running" OR "run" OR "sprint" OR "sprinting" OR "jog" OR "jogging") AND ("gait" OR "stride" OR "treadmill")

Inclusion criteria of the initial screening were: Human subjects, running related experiment, computed LRC analysis on running, and must be an experiment. Studies on animals, non-humans, walking only, non-running, non-LRC analysis, and non-experiments (systematic reviews, meta-analysis', theoretical frameworks, etc.) were removed. The initial screening was done by two investigators (TW and AL), and an initial article selection was identified by the title and abstract, while reviewing full text if necessary, using the systematic review device Rayyan (Qatar Computing Research Institute) [47]. Screeners were blinded to each other's evaluations. Conflicts about inclusion and exclusion decisions were resolved by deliberation between the two investigators (TW & AL).

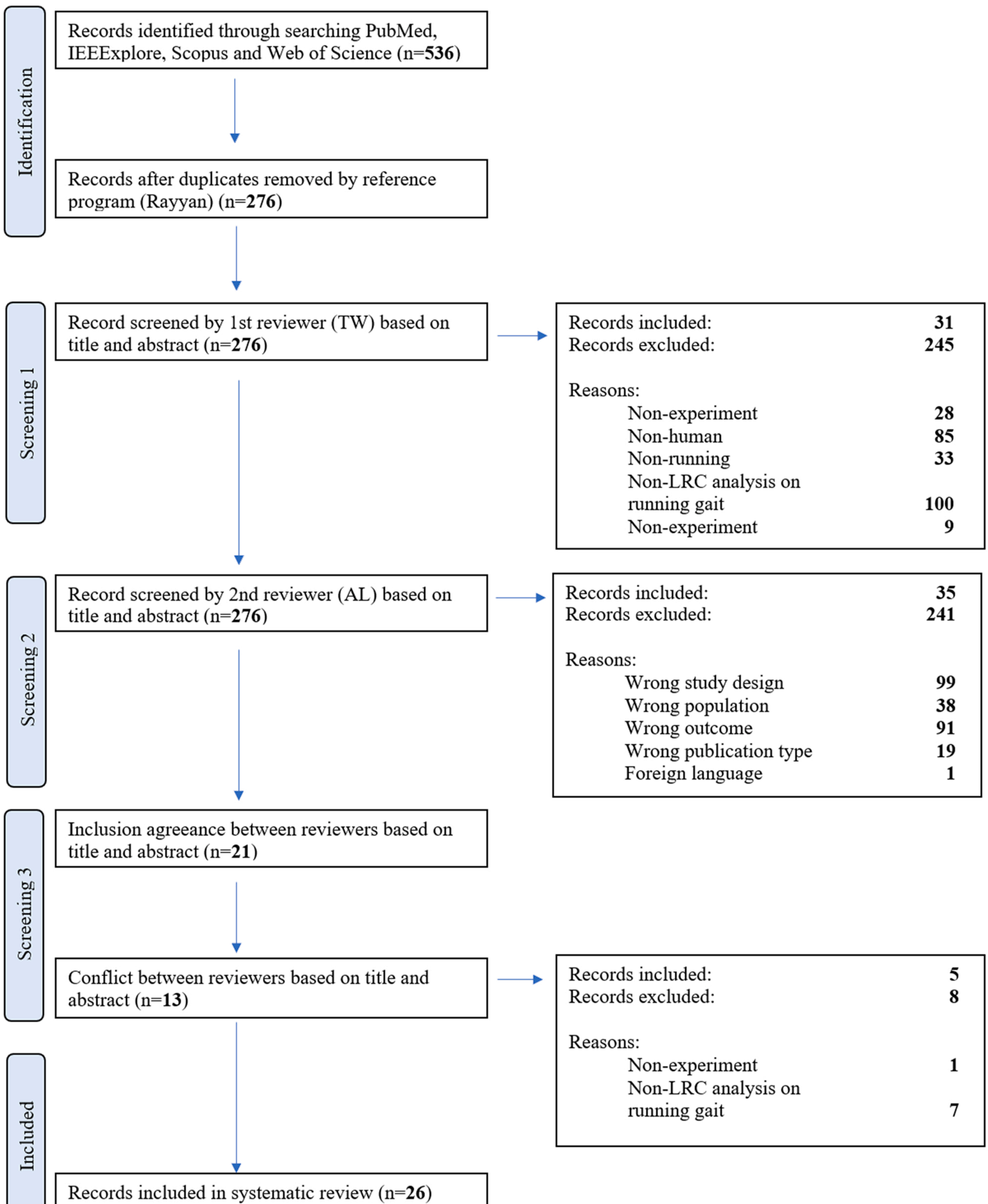

Fig. 2. Article search and screening process.

Once the final articles were selected for review, a quality assessment was performed based on methods in previous literature [48], and tailored to the specific aims of this systematic review:

1. Sample size greater or equal to 10.
2. Specified inclusion/exclusion criteria of research participants.
3. Defined the protocol.
4. Defined the surface on which the subjects locomoted.
5. Specified aim/purpose of study.
6. Specified long-range correlations.
7. Used a minimum of 600 strides when utilizing non-linear analyses.

For each item on the list, papers were scored with a 1 for meeting the criteria or a 0 for not meeting the criteria. Papers that received a *Quality of Assessment Score* (QAS) of 6 or above received a rating of "high quality", a QAS of 4 or 5 were deemed a rating of "medium quality" and papers a QAS of 3 or lower were categorized as "low quality". The score given in this systematic review does not reflect the overall ability of the articles to assess the subject(s) but gives a qualitative interpretation of the study design, in addition to methodological reliability when calculating and explicating the LRCs regarding running gait. (Fig. 2).

3. Results

After removing duplicates from the initial 536 search results, 276 studies were identified based on our search terms (Fig. 2). Two reviewers (TW & AL) conducted blind reviews on the 276 articles in Rayyan based on title and abstract alone. While TW excluded 245 articles (31 included articles), AL excluded 241 articles (35 included articles). A deliberation meeting was held to resolve the five-article difference. TW and AL initially agreed on the inclusion/exclusion of 21 articles. Based on reading the full text of the 13 articles that produced a conflict of inclusion and exclusion, five articles were included and eight were excluded. After a unanimous decision between TW and AL, the final selection of 26 articles were included based on title, abstract and full text.

Of the 26 included articles, 21 articles looked at the LRCs of treadmill running alone [16,28,49–67], three articles looked at overground running alone (two articles tested on an oval track [68,69], and one article tested on multiple half-marathon racecourses [27]), and two articles compared treadmill and overground running (one article tested on an oval track [70], while the other tested on a straight overground surface [71]). The mean number of participants among the 26 studies was 20.7 participants, and ranged between 1 [61] and 90 [57]. The average trial length was 9.5-minutes, and ranged from one minute [55] to 97 min and 35 s [27]. Twenty-two articles used DFA [16,49–66, 68–70], while the remaining articles used the FD [27], HFD [28,67], or R/S [71]. Lastly, our quality assessment revealed 20 high quality articles [16,27,28,49,50–52,54,55–59,62,63,65,66,68,69,71] and 6 medium quality articles [53,60,61,64,67,70] based on the QAS given to each article (*Supplementary Excel File – Quality Assessment*).

LRC characteristics of running gait were apparent in 24 articles [16, 27,28,49–64,66,66,68–70], based on statistical output values explicitly, but are not apparent in two articles [65,67]. LRCs in *stride length* (SL) were similar for both elite and recreational runners, $\alpha = 0.80 \pm 0.12$ and $\alpha = 0.83 \pm 0.12$, respectively [68]. In agreeance, Panday and colleagues found no difference in LRCs between expert and novice runners for SL, *stride time* (ST), and *stride width* (SW) at each 5-minute interval of observation (P1: 0 – 5 min, P2: 5 – 10 min, P3: 10 – 15 min, P4: 15 – 20 min) [66]. While walking gait α tended to increase with an increase in locomotion speed, the α in running gait tended to decrease with an increase in locomotion speed [16]. Another article by Jordan and colleagues [53] found LRCs fit a U-shaped curve in relation to running speed, where the *stride interval* (SI) LRCs of running gait were higher at slow ($\alpha \sim 0.89$) and fast speeds ($\alpha \sim 0.85$) relative to preferred running speed (PRS, $\alpha \sim 0.78$). LRCs were also apparent during the transition speed from walking to running (ankle marker $\alpha = 0.74$; head marker $\alpha = 0.81$) and during transition speed from running to walking (ankle marker $\alpha = 0.72$; head marker $\alpha = 0.73$) [16]. Additionally, one article found that the LRCs between the left, $\alpha = 0.885$, 95% confidence interval (CI) = (0.834, 0.935) and right leg $\alpha = 0.884$, 95% CI = (0.834, 0.933), were highly symmetrical [59].

Heavy training and overreaching states tended to influence the LRCs of running gait. Bellenger and colleagues [50] and Fuller and colleagues [52] both examined the effects of heavy training on the LRC characteristics in running gait. A significant decrease in α due to heavy training was reported at 65% *maximum heart rate* (HRmax) ($\alpha = 0.68 \pm 0.13$) compared to baseline ($\alpha = 0.80 \pm 0.09$), but not at 85% HRmax ($\alpha = 0.71 \pm 0.22$) compared to baseline ($\alpha = 0.74 \pm 0.09$) [50]. Changes in α at 65% HRmax also correlated with changes in the *Daily Analysis of Life Demands for Athletes* (DALDA) questionnaire ($r = -0.52$; $p = 0.021$) but did not correlate at 85% HRmax ($r = 0.16$; $p = 0.0517$) [50]. In agreeance with Bellenger and colleagues, albeit not significantly, Fuller and colleagues [52] found that α decreased for treadmill running after heavy training at 10.5 km/h ($\alpha = 0.61 \pm 0.06$) compared to light training at the same speed ($\alpha = 0.66 \pm 0.05$), and found no effect of training ($\eta^2 = 0.07$, $p = 0.55$) or speed ($\eta^2 = 0.05$, $p = 0.65$) on the SI LRCs in running gait.

Load carriage, as a percent of *bodyweight* (BW), also influenced the LRCs of running gait. One study by Krajewski and colleagues [55] compared the LRCs in running gait versus marching gait at 100% BW, 125% BW, and 145% BW. While running gait on the treadmill exhibited an α close to pink noise for both SL ($\alpha = 0.88 \pm 0.31$) and ST ($\alpha = 1.04 \pm 0.50$) for 100% BW; LRCs tended to decrease as load magnitude increased to 125% BW (SL: $\alpha = 0.63 \pm 0.26$, ST: $\alpha = 1.09 \pm 1.02$) and 145% BW (SL: $\alpha = 0.27 \pm 0.63$, ST: $\alpha = 0.15 \pm 0.54$) [55]. Another study by Krajewski and colleagues [65] compared the LRCs in running gait versus marching gait at 100% BW, 125% BW, and 145% BW; but ran DFA on *joint work* (JW) at the ankle, knee, and hip. In opposition to the previous article [55], Krajewski and colleagues found α tending away from 1 (decrease in LRCs) at 100% BW for both positive JW (JWpos) at the ankle (α = 0.63 ± 0.26), knee (α = 0.36 ± 0.51), and hip (α = 0.81 ± 0.76) and negative JW (JWneg) at the ankle (α = 0.58 ± 0.25), knee (α = 0.40 ± 0.44), and hip (α = 0.69 ± 0.59), respectively [65]. Although not statistically analyzed in the article, α means tended to decrease when BW increased to 125% BW for JWpos at the ankle (α = 0.37 ± 0.75), knee (α = 0.22 ± 0.81), and for JWneg at the ankle (α = 0.38 ± 0.73) and knee (α = 0.31 ± 0.85), but not for JWpos at the hip (α = 1.00 ± 0.52) or JWneg at the hip (α = 0.77 ± 0.42). Further, 145% BW α means tended to decrease compared to 100% BW for all JWpos at the ankle (α = 0.19 ± 0.93), knee (α = 0.05 ± 0.82), and hip (α = 0.79 ± 0.75) and for all JWneg at the ankle (α = 0.24 ± 0.89), knee (α = 0.27 ± 0.83), and hip (α = 0.66 ± 0.54). To note however, there are high standard deviation values of α for all JW α, ranging from 0.25 to 0.93.

Fatigue seemed to influence LRCs over time. Four articles looked at the effects that fatigue had on the LRCs in running gait [27,58,68,69]. LRCs decreased over time during a prolonged overground run to exhaustion for both SL in experienced (beginning $\alpha = 0.89 \pm 0.15$, end $\alpha = 0.77 \pm 0.08$) and recreational runners (beginning $\alpha = 0.91 \pm 0.14$, end $\alpha = 0.77 \pm 0.13$) and for ST in experienced (beginning $\alpha = 0.86 \pm 0.09$, end $\alpha = 0.73 \pm 0.14$) and recreational runners (beginning $\alpha = 0.84 \pm 0.11$, end $\alpha = 0.73 \pm 0.14$) [68]. This agreed with Meardon and colleagues [69], in which an overall decrease of LRCs was found over the course of the run for both injured (beginning $\alpha = 0.92$, middle $\alpha = 0.68$, end $\alpha = 0.77$) and non-injured runners (beginning $\alpha = 1.19$, middle $\alpha = 0.86$, end $\alpha = 0.85$). Mo & Chow [58] found a U-shaped trend in α for SI in both experienced runners (beginning $\alpha = 0.74 \pm 0.07$, middle $\alpha = 0.67 \pm 0.09$, end $\alpha = 0.75 \pm 0.10$) and novice runners (beginning $\alpha = 0.72 \pm 0.07$, middle $\alpha = 0.64 \pm 0.10$, end $\alpha = 0.69 \pm 0.08$) over a prolonged run. However, that difference is not straightforward. Only injured runner's displayed a somewhat U-shaped trend in

α – non-injured runners exhibited a more pronounced linear trend [69].

Reported effects of speed reflect a mixture of trends when comparing PRS to higher or lower speeds. Seven articles looked at the LRCs of PRS and at different percentages of PRS [53,54,56,60,61,63,70]. Four out of the seven articles looking at PRS [53,54,61,70], indicated that LRCs are reduced at PRS (U-shaped trend), compared to Mann and colleagues [56] who found an opposite trend. Further, Nakayama and colleagues [60] showed that while the non-runner group showed a U-shape trend of α at 80% ($\alpha \sim 0.92$), 100% ($\alpha \sim 0.90$) and 120% PRS ($\alpha \sim 0.93$), the experienced runner group claimed that α increased as PRS increased, from 80% ($\alpha \sim 0.75$) to 100% ($\alpha \sim 0.78$) then to 120% PRS ($\alpha \sim 0.79$), but did not reach statistical significance. Walsh found no differences between PRS and 120% PRS in the anterior/posterior, medial/lateral, or vertical positions when measuring LRCs at the center of mass and in motor primitives measured by muscle synergies [28].

Speed effects also show a mixture of trends at different critical velocities (CV, different than the PRS metric) [64] and at specific running speeds ranging from 2.0 m/s to 3.5 m/s in long distance runners and from 4.2 m/s to 9.5 m/s in sprint athletes [67]. One article looked at α values at the ankle, knee, and hip during 95%, 100%, 105%, and 115% CV, where exercise above CV is characterized by metabolic flux and systemic responses to exercise and below CV represents a steady state to attain exercise for a prolonged period of time [64]. Hunter and colleagues applied DFA to the steadiest 20 s epochs in the beginning and end of a 20 min run at 95%, 100%, 105%, and 115% CV. Overall, a decrease in LRCs was found at 115% CV, compared to lower velocities at the ankle, knee, and hip. In addition, the only difference in LRCs between the beginning and end of the run occurred at knee internal and external rotation at 95% CV (beginning $\alpha = 0.631 \pm 0.071$ and end $\alpha = 0.660 \pm 0.072$) and at 100% CV (beginning $\alpha = 0.624 \pm 0.066$ and end $\alpha = 0.640 \pm 0.067$). Lastly, one article looked at LRC changes between running speeds at 2.0, 3.0, and 3.5 m/s in recreational long-distance runners and the LRC changes between running speeds at 2.8, 4.2, 5.6, 6.9, 8.3, and 9.5 m/s in sprint athletes [67]. In recreational runners, Santuz and colleagues found a decrease in LRCs from 2.0 m/s (HFD ~ 1.18) to 3.0 m/s (HFD ~ 1.13). A decrease in LRCs with an increase in speed was also found in the sprinting group from 2.8 m/s (HFD ~ 1.17) to 9.5 m/s (HFD ~ 1.14), but no significant differences in LRCs were found between 4.2 m/s and 5.6 m/s, 6.9 m/s and 8.3 m/s, and 8.3 m/s and 9.5 m/s.

LRCs were apparent in running gait for all surfaces and interfaces between the surface in one study [70], while LRCs were not found on either surface in accordance to another study [71]. Treadmill running produced higher LRCs ($\alpha = 1.02 \pm 0.18$) compared to overground running ($\alpha = 0.85 \pm 0.15$) [70]. Given the constant speed and pace of locomoting on a treadmill, it's not surprising that human gait would exhibit LRCs that are different than an overground environment. The treadmill environment produces constraints on the system, due to the constant speed, straight path, and size of the treadmill. This limits the available degrees of freedom and solutions the system can use to produce the required outcome of running stably, yet adaptively on a treadmill environment. However, the direction of LRCs was surprising, and is at odds with walking gait [22]. One might have expected that because treadmills act as a constraint or pacing device, then the LRCs would be weakened as is seen in walking gait [22,72,73]. If the results were to replicate, such findings would raise theoretical questions about how pacing affects LRCs in gait. Agresta and colleagues [49] used a combination of treadmill and metronomes but found little effect of metronomes, possibly because the pacing from the treadmill is such a heavy-handed constraint. Indeed, an interesting follow up experiment would be to investigate how pacing signals (e.g., metronomes) affect overground running gait. In contrast to Lindsay and colleagues [70], Mileti and colleagues used R/S on motor primitives that produced lower H values on a treadmill (H ~ 0.30) compared to an overground environment (H ~ 0.35) [71]. Further, H values for both treadmill and overground running were lower than 0.5, signifying no LRCs when measuring at motor primitives. Based on the findings between these two articles [70,71], it is unclear if the trend of higher LRCs in a treadmill surface hold true compared to an overground surface, or if the lack of LRCs found in both environments holds true. To note, LRCs were detected differently where Lindsay and colleagues applied DFA to stride time series [70], where Mileti and colleagues applied R/S to motor primitives [71], in which could affect the accuracy of detecting LRCs.

In addition to surface, LRCs were apparent for different interfaces of traversal and landing technique. Fuller and colleagues [51] and Mann and colleagues [57] concluded that LRCs were apparent in the interface of both *minimalist shoes* (MS) and *conventional shoes* (CS). These articles [51,57] showed no significant differences in LRCs between subjects using MS versus CS. Additionally, Garofolini and colleagues found no difference in LRCs between a low minimalist index (MI) shoe (MI = 18%), medium MI shoe (MI = 56%), and high MI shoe (MI = 96%); where MI is defined from 0 (maximum assistance) to 100% (least assistance with the foot) [63]. This article also looked at the difference in LRCs in leg stiffness between forefoot strikers (FFS) and rearfoot strikers (RFS) at touch-down (0.2–1BW), loading (1BW to peak ground reaction force (GRF)) and unloading phases (peak GRF to 0.2BW). FFS had higher LRCs than RFS only at the touch-down phase (FFS $\alpha \sim 0.68$ vs RFS $\alpha \sim 0.60$). Further, there was a difference in LRCs for FFS between touch-down ($\alpha \sim 0.68$) and loading ($\alpha \sim 0.64$) and between loading ($\alpha \sim 0.64$) and unloading phases ($\alpha \sim 0.73$). On the other hand, RFS showed no difference in LRCs between all three phases.

Injury rate is a big obstacle in terms of running gait, where at least 50% of runners obtain an injury in a year [74]. Only a couple of articles in our search touched upon the effects of injury on LRCs, in which two articles [69,70] found conflicting results. Mann and colleagues [56] found a higher α in previously injured runners than non-injured runners from 80% to 110% PRS, but the difference in ST α was not significant. This disagreed with Meardon and colleagues [69] who found that previously injured runners demonstrated lower LRCs overall ($\alpha = 0.79$) compared to non-injured runners ($\alpha = 0.96$).

4. Discussion

The overarching goal of this systematic review was to document the state of the art concerning LRCs in running. In particular, we aimed to identify typical ranges of α in running gait, understand differences in α across tasks (e.g., walking and running), as well as how running gait LRCs might be altered in other cases such as disease and injury. Ultimately, our review of the literature may have returned too few studies to rigorously address that aim; however, we feel that these results point to a large opportunity for future research given that so little is known about LRCs in running gait. Without exception our results showed that the typical LRCs of running gait tend to exhibit α close to 1.0 and, in that sense, mimic the ubiquity of LRCs found in walking gait. Importantly, the literature also suggests that the strength of LRCs depends on context. For example, LRCs in running gait seem to depend on speed in a nonlinear way with deviations away from PRS producing slightly higher α than PRS. Moreover, fatigue tends to reduce the strength of LRCs, although fatigue effects may depend on the expertise of the runner. As a caveat, we note that most of the studies included in our review were mostly on LRCs found in treadmill running. Hence, interpretations of trends may have limited generality outside that domain. The remainder of this discussion is organized as follows: First, we address how the observed trends in the literature align with the OMVH, articulating areas of convergence and apparent divergence. Second, we discuss potential implications of our results from clinical/rehabilitative perspective. Third, we propose several future directions that need to be engaged in order to move this line of research forward.

4.1. *Running Gait LRCs in the context of human movement variability*

Distilled, the OMVH makes key predictions about those that may be considered optimal patterns of variability. Optimal patterns, typified by pink noise, represents a “sweet spot” that balances complexity and predictability to putatively allow for flexibility and adaptability as the context of movement changes. As such, a following prediction is that the “default mode” of locomotion should likewise exhibit pink noise. The experimental data returned in our search provides strong evidence in support of that claim. Almost unanimously, those papers demonstrate that, like walking gait, healthy young adults adopt running gait variability patterns that are well described as producing LRCs, with αs that tend towards one. That is, in agreement with the OMVH, the “default mode” in running seems to exhibit patterns consistent with pink noise.

The OMVH also predicts that non-optimal patterns of variability should deviate away from characteristic pink noise, deviating in one of two directions – either becoming overly random or overly predictable. Evidence from fatigue-related research likewise supports this prediction [52,69,75]. For example, increasing physical stress due to load carriage drastically reduces LRCs, producing anticorrelated patterns in spatiotemporal gait features when participants donned 145% their body weight [55]. Similarly, some authors have demonstrated that fatigue tends to reduce the strength of LRCs in running when measured over the time course of long running protocols in both overground [68,69] and treadmill environments [64], but others suggest no significant decreases in LRCs on a treadmill environment due to fatigue [57,58]. In short, LRCs decreased due to fatigue, but predominately in an overground environment. Moreover, heavy training also seems to reduce the strength of LRCs [50]. The implication across those findings is that, as physical stress becomes more extreme, as likelihood of fatigue increases, the runner becomes less adaptable. Consistent with the OMVH, fatigue may induce deviations away from optimal movement variability, as evident from reductions in LRCs.

So far, we have interpreted evidence in our review in positive support of the OMVH. Those interpretations, however, are not without exception. Given predictions of the OMVH, one might speculate running variability should be optimal at PRS. If that were the case, then one would likewise anticipate that deviations from PRS should produce deviations from optimality similar to those reported in the context of fatigue above [55], i.e., an inverted-U shaped function relating speed to α. The papers returned in our review did return a concave trend but not in direction specified by the OMVH. That is, most articles showed that α was lowest at PRS and tending higher at running speeds slower and faster than PRS (Table 1) [53,54,61,70]. Another paper in our review that investigated the fractal dimension of center of mass variability found no differences between PRS and 120% PRS in either walking or running [28]. Consequently, most effects of speed seem to contradict a central concept of the OMVH.

An important feature of the aforementioned studies, though, is that most studies took place on a treadmill [53,54,61,70]. Treadmills are known to influence gait dynamics in walking, reducing α observed from spatiotemporal gait features relative to overground walking [22]. One article we reviewed compared treadmill and overground running and found that treadmill running produced higher α than overground running, at all speeds [70]. Thus, an alternative explanation for the speed effects is that the observed U-shaped functions relating speed and

Table 1
α as a function of surface and preferred running speed (PRS).

		PRS				
Article	Surface	80%	90%	100%	110%	120%
Norris et al. 2016	Treadmill	0.85	-	0.80	-	0.92
Jordan et al. 2006*	Treadmill	0.86	0.83	0.73	0.77	0.76
Jordan et al. 2007*	Treadmill	0.89	0.82	0.78	0.83	0.85
Lindsay et al. 2014	Treadmill	1.04	-	0.98	-	1.05
Lindsay et al. 2014	Track	0.86	-	0.86	-	0.85

Note. Reported α are means or approximate means (*), with “-“ indicating no data at that PRS.

α reflect a nonlinear interaction between running speed and altered dynamics elicited from constraints of treadmill running. Lindsay and colleagues [70] investigated that question and found little evidence of such an interaction. Instead, it is possible that higher α in treadmill environments compared to overground environments is related to the speed constraints of locomoting on a treadmill. Because speed cannot be varied easily on the treadmill (speed control is effectively off-loaded to the treadmill belt), the motor system may prefer a more structured gait pattern to complete the task of running on a treadmill because the environment is more predictable. Large α (close to 1) may reflect that tendency. However, that explanation is also strained because α also seems to increase at speeds slower than PRS [53,54,61,70]. Clearly, more research is needed to discern if surface and speed combine to produce alterations to gait dynamics. Regardless, treadmill running at speeds different than PRS remain a challenge for the OMVH to explain.

4.2. *Running Gait LRCs in clinical settings and rehabilitation*

The seeming ubiquity of LRCs in running gait leads us to question why little work has been conducted on the topic from a clinical perspective. Our search failed to return any articles that measured the effect of disease on running gait LRCs. Perhaps this is not surprising. Individuals with neurodegenerative diseases often have difficulty walking for more than a few minutes, let alone running. Lack of data on running LRCs in clinical populations is further complicated by challenges in measuring LRCs in short time series [76,77]. Despite those challenges, we argue that, when possible, to collect sufficient data (e.g., early stages of disease progression), LRCs in running gait could provide additional diagnostic power for early detection of disease. For example, one large scale study investigating LRCs derived from long term activity data found that reductions in LRCs often preceded typical clinical presentations of neurological symptoms [78–80]. Given the relative physical demand of running compared to walking, altered dynamics may be present sooner in running than walking gait. In that sense, further investigation of how running gait dynamics change over the time course of disease could provide early warning signals of disease onset, particularly in those people that run daily.

Furthermore, investigations into the evolution of running gait dynamics over time could provide insight into early warning signs of injury onset and promote injury prevention. One meta-analysis reported that injury prevalence in runners lies between 19% and 79% [81]. Others have noted annual injury rates of up to 52% [82]. There are also studies that hint at a relationship between injury and altered LRCs. For example, LRCs have been shown to decrease due to injury status [69], declining physical function [14], and have also been shown to decline and remain low up to ten days after functional overreaching [50,52]. Further, LRCs decreased significantly during a prolonged run right before the onset of fatigue [68] – while running when fatigued increases injury rate [83]. Combined, those studies imply that LRCs may decrease right before injury onset. Although we are optimistic that measurement of LRCs could assist in injury detection, more research is needed to support our optimism. Our search only found two papers that compared previously injured versus non-injured runners and those studies produced conflicting results. One paper [69] found lower LRCs in injured runners during a prolonged run ($\alpha = 0.79$) compared to non-injured runners ($\alpha = 0.96$), but the other [56] found no reliable differences in LRCs between injured and non-injured runners. Clearly, more research is needed that makes direct comparisons between injured and non-injured runners to evaluate the utility of LRCs as a running injury diagnostic tool.

4.3. *Needed: future research on LRCs in running gait*

Our review of this literature suggests a number of areas that would be fruitful topics for future research. Some topics relate to resolving confusing trends in the literature. These trends include surface effects on

LRCs (treadmill versus overground), overground surface effects on LRCs (sand, gravel, dirt, cement, etc.), jogging versus sprinting LRCs, asymmetries in LRCs between the left and right leg, speed, and fatigue effects on overground LRCs, and the healthy range of LRCs (α) in running gait. Overall, LRCs were found in running gait, but more research should be conducted to support the trends that were found in the current literature.

It is apparent that most of the articles in this systematic review investigated LRCs in a treadmill environment (23/26 articles) compared to an overground environment (5/26 articles). As apparent by the artificiality of a treadmill environment, the constraints (fixed speed, surface stiffness, space given for locomotion) placed on the system could have an influence on the emergent properties of LRCs. While some literature state similarities between treadmill and overground running in terms of the temporal characteristics of stance and stride [84] and level surface running kinetics [85]; others found differences in terms of uphill and downhill running kinetics [85] and level surface running kinematics [86]. The locomotive environment may potentially have an ineffective role in LRCs due to the rapid adjustment of leg stiffness (underlying physiological response) to offset surface stiffness [87]. Further, given that the treadmill represents an artificial environment and hence constraining the system's ability to adapt, one might state that detecting LRCs in a treadmill environment is not worthwhile. However, because treadmills are pervasive in both medical settings (i.e., physical therapy, cardio stress tests, etc.) and daily life (largely due to convenience), one might argue that it is crucial to understand how gait is modified when running (or walking) on a treadmill. Taken together, it is useful to determine if the differences in LRCs found between these two environments [70], and the typical LRCs on an overground surface, hold true. In addition, we highlight below several issues for future research that may be limiting the presence of strong trends in the literature.

A critical aspect of future research involving LRCs in running is the application of non-linear analyses on time series of sufficient length and appropriate type. For instance, it has been found that > 500 data points is recommended for the commonly used DFA algorithm to detect LRCs with an accuracy of $\alpha \pm 0.1$ [76,88]. Furthermore, DFA tends to be positively biased, an effect exacerbated by short time series, suggesting that large αs observed in some contexts could be explained by such issues. Nearly half the studies in our review, 11 out of 26 articles, failed to meet this minimum amount of data points [50–52,55–58,64,65,67,69]. Furthermore, DFA assumes time series do not have dominant frequencies (i.e., not cyclical, like joint angles). However, several articles we reviewed used DFA on cyclical data [28,64,65,67,71], so the results of α and interpretations of LRCs are questionable. Additionally, there is considerable inconsistency in terms of the input variables from which LRCs were estimated, producing different outcomes and interpretations depending on which variable one investigates. For instance, in one study [63], GRF α was different than leg effector length α and leg stiffness α during touch-down ($\alpha \sim 0.53$ vs $\alpha \sim 0.63$ and 0.66, respectively), loading ($\alpha \sim 0.70$ vs $\alpha \sim 0.65$ and 0.61, respectively), and unloading phases ($\alpha \sim 0.77$ vs $\alpha \sim 0.66$ and 0.70, respectively). Thus, new experiments, as well as replications, are needed to address potential methodological confounds and inconsistencies present in the running literature concerning LRCs. The inconsistencies of variable type (GRF, leg stiffness, joint angle, stride intervals, etc.) and improper statical utilization populate the literature on LRCs, for which comparisons between studies and the interpretation of LRCs becomes confusing, confounded, and unreliable at times.

Of course, it is likewise possible that the lack of strong trends or patterns in the manuscripts we reviewed carries a stronger message. Perhaps LRCs are simply not a meaningful metric of running health. However, we would argue that statement may be premature. Our hesitance to draw that conclusion is based on at least two sets of facts. First, LRCs have proven useful in characterizing walking gait for decades, distinguishing health from pathology as well as articulating differences in experimental conditions [6,8,9,11,14,15,20–22]. It would be genuinely surprising and portend serious theoretical consequences were LRCs to be relevant for one aspect of gait but not another. Second, we have highlighted several inconsistencies in the literature that make synthesizing the state of the art challenging. We contend that more research is needed with careful selection of input variables and watchful attention to assumptions of time series analysis tools.

5. Conclusion

The goal of this systematic review was to evaluate the state of the art concerning LRCs in running. To do so, we identified articles that measured the LRCs of running gait, along with the effects that injury, speed, and surface have on running gait LRCs. Without exception our review found that running gait exhibits strong evidence of LRCs, a finding consistent with trends observed in walking gait [1,2,6–17,20,36]. Moreover, we found that measures of LRCs tend to negatively correlate with fatigue. Although LRCs at the preferred running speeds support major aspects of the OMVH, increased LRCs during treadmill running at speeds different than PRS present a challenge for the model to explain. Based on our review, we contend that the field would benefit from systematic investigations of LRCs in the context of overground running, injury, shod and barefoot running, and differing support surfaces. Given the apparent ubiquity in running, a better understanding of the LRCs could aid in injury prevention, increase performance, and potentially detect the onset of diseases in avid runners.

CRediT authorship contribution statement

Taylor Wilson: Conceptualization, Software, Validation, Formal Analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Aaron Likens:** Conceptualization, Methodology, Validation, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Visualization, Funding acquisition.

Conflict of Interest

None.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gaitpost.2023.04.001.

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