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The Application of non-linear methods to quantify changes to movement dynamics during running: A scoping review

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ABSTRACT
The aim of this scoping review was to evaluate research approaches that quantify changes to non-linear movement dynamics during running in response to fatigue, different speeds, and fitness levels. PubMed and Scopus were used to identify appropriate research articles. After the selection of eligible studies, study details and participant characteristics were extracted and tabulated to identify methodologies and findings. Twenty-seven articles were included in the final analysis. To evaluate non-linearities in the time series, a range of approaches were identified including motion capture, accelerometery, and foot switches. Common methods of analysis included measures of fractal scaling, entropy, and local dynamic stability. Conflicting findings were evident when studies examined non-linear features in fatigued states when compared to non-fatigued. More pronounced alterations to movement dynamics are evident when running speed is changed markedly. Greater fitness levels resulted in more stable and predictable running patterns. The mechanisms by which these changes are underpinned require further examination. These could include the physiological demand of running, biomechanical constraints of the runner, and the attentional demands of the task. Moreover, the practical implications are yet to be elucidated. This review has identified gaps in the literature which should be addressed for further understanding of the field.

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Non-linear analysis; running; fatigue; review

Introduction

Running is typically considered as a sequence of cyclical movements that allow humans to navigate their environment (Novacheck, 1998). The result of the integration of feedforward and feedback control in a healthy and unfatigued system is a stable gait and consistent movement pattern (Kiely, 2017). Whilst healthy gait is often characterised as smooth and repeatable, fluidity of gait is a result of the interaction of numerous complex systems, including activation patterns of muscle groups and the integration of sensory information (Santuz et al., 2018). The reductionist view of the smoothness of systems and the repeatability of movement ignores the complexity of the structure and function of smaller subcomponents. Indeed, many seemingly constant facets of human physiology are fundamentally complex and exhibit variability, including heart rate (Goldberger et al., 2002), blood pressure (Wagner et al., 1996), and force production (Pethick et al., 2015). Previously, complexity and variability were thought of as mere noise, often filtered and ignored during analysis (Goldberger et al., 2002). However, during the past three decades, noise has been recognised more widely as a means of conveying important information about the functional status of a system during gait (Mehdizadeh, 2018; Stergiou & Decker, 2011; Stergiou & Stergiou, 2018; Strongman & Morrison, 2020).

Within gait, there are many characteristics that can be analysed to assess temporal variability to give an insight into motor control of gait, including stride time (Meardon et al., 2011), joint angle data (Hunter et al., 2021), as well as segmental accelerations (Rabuffetti et al., 2019). Classically, gait features during running and walking are assessed using discrete measures, e.g., peak joint angles or stance time. Linear measures such as standard deviation or coefficient of variation are useful for examining the magnitude or variability of these measures from the mean but ignore the temporal dynamics of variability and treat each stride as an independent process. This approach fails to acknowledge the role of the feedback loop that determines motor commands in each stride which may affect subsequent strides (Meardon et al., 2011). The recognition of the complexity of gait has led investigators to employ different techniques from chaos and information theory to better understand movement dynamics Within the study of gait, there exist numerous parameters that warrant investigation. Similarly, various non-linear approaches exist for the assessment of dynamical systems, reduced in this review to stability, complexity, and fractal scaling. Local dynamical stability of gait is commonly assessed by the largest Lyapunov exponent (LyE) and quantifies the rate of divergence or convergence to a trajectory in a state space, interpreted as the ability to compensate to small perturbations (England & Granata, 2007). The regularity or predictability of a system can be quantified by calculating the entropy of a time series (Yentes & Raffalt, 2021). Detrended fluctuation analysis (DFA) is used to detect long-range correlations or

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statistical persistence which reveal self-similar fractal scaling in a time series (Hausdorff et al., 1995).

While several reviews have been compiled to evaluate the application of non-linear analysis methods to examine gait dynamics and its potential to evaluate disease severity, ageing, or injury (Hausdorff, 2007; Mehdizadeh, 2018; Strongman & Morrison, 2020), none has attempted to delineate the use of non-linear analysis methods to identify differences in motor control related to fatigue, different movement speeds, and fitness levels. A better understanding of the approaches taken may go some way to improving understanding of how movement dynamics are mediated during running. Therefore, this scoping review will evaluate the approaches taken to quantify changes to non-linear movement dynamics in response to fatigue or speed. Moreover, the review will also examine how changes to movement dynamics can be measured in populations with differing fitness levels. A summary of directions for future investigations will be outlined and potential practical applications will be identified.

Materials and methods

The scoping review was conducted in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) checklist (Tricco et al., 2018).

Search strategy and study selection

PubMed and Scopus were searched for peer-reviewed articles related to the stability, complexity, and fractal scaling of gait dynamics. Search terms included were:

(variability OR *stability OR complexity) AND (nonlinear OR non-linear OR fluctuat* OR entropy OR autocorrelation OR chao* OR lyapunov) AND (gait OR run* OR jog*).

Reference lists from identified articles and citation tracking on Google Scholar were used as a supplementary search technique. Following the widened search, results were imported into a reference manager (Mendeley Desktop Version 1.19.8, Mendeley Ltd., London, UK). To be included in the review, papers needed to measure non-linear dynamics in running. Accordingly, the inclusion criteria were: (i) studies on running, (ii) English language articles, (iii) studies using healthy adults or adolescents, and (iv) using non-linear analysis. The exclusion criteria were: (i) movements other than running, (ii) non-English articles (due to anglophone reviewer), (iii) conference proceedings or grey literature, (iv) modelling or simulation studies, and (v) reviews. Healthy control group data from research articles studying amputees or prosthetics, injured populations, and older adults were included when screening titles or abstracts. In cases where a healthy control group was examined, only the data from this was used for further description. Studies that examined electromyography were only considered if part of an investigation examining other facets of movement dynamics, such as angular kinematics. Reference lists of reviews from the initial search were searched for relevant sources. Initial database search was performed on 14 April 2021 with an updated search conducted on 1 September 2022.

One reviewer (BH) assessed the eligibility of the studies. Titles and abstracts were reviewed and publications that were deemed not appropriate were excluded from the review. Full manuscripts of articles that met the inclusion criteria were obtained and reviewed in full. To ensure consistency and reliability of the individual reviewer, the full texts were reassessed by the same reviewer, and the agreement percentage between the initial and subsequent assessments was calculated (96.4%).

Data extraction and synthesis

Data were extracted on study population characteristics (location, sex, age, body mass, stature, and fitness levels), study characteristics (sample size, surface, task, setting), and methods used to measure non-linear dynamics (equipment used to track movement and location if applicable, sampling frequency of data collection, measures taken, and algorithm(s) used). Differences in the regularity, randomness, fractal scaling, task constraint, or stability were extracted when a statistically significant difference was identified between speeds, task time, or fitness level ($p < 0.05$). Following data extraction, data were tabulated and reported descriptively to address the aims of the review. Consistent with guidance on scoping review conduct (Peters et al., 2015), methodological quality and risk of bias of the included studies were not evaluated.

Results

Search results

The search results retrieved are presented in Figure 1. The initial search generated 4193 research articles. Following the removal of duplicates, a total of 4182 records were left for title and abstract screening which resulted in 72 remaining records. No additional research articles were found through the manual search of reference lists. Following the assessment of the inclusion and exclusion criteria, full text review led to 27 articles being included in this review.

Participant characteristics

A summary of sample characteristics for included studies is given in Table 1. Most studies included male participants (24/27; 88.9%), whereas only 59.2% (16/27) included female participants. Of the 27 articles reviewed, 13 included a mixture of male and female participants, 11 recruited only male participants, and only three reported using only female participants. No studies that excluded either male or female participants provided rationale. From the 27 studies which reported the number of males and females, these in total were 352 (70.8%) and 145 (29.2%), respectively. Most studies included participants aged ≥18 years, with one study examining adolescents (Murray et al., 2017). Where anthropometric characteristics were reported, participants' mean body mass, stature, and age were 67.9 kg, 1.75 m, and 26.6 years, respectively. Studies examined participants with a variety of different fitness or skill levels. Seven studies examined gait in recreational runners, five recruited trained or experienced runners, with six examining both recreational and experienced runners. Of the six studies which recruited recreational and experienced runners, four compared movement between groups. Eight studies did not

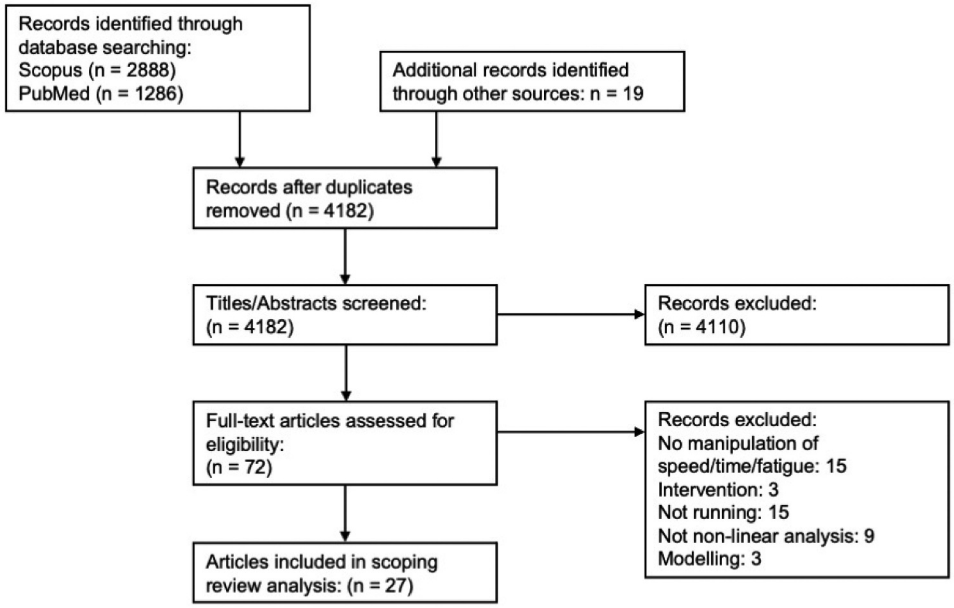

Figure 1. PRISMA flow diagram of the search strategy and screening of identified research for inclusion (Page et al., 2021).

describe the level of runners recruited, and one study assessed gait in team sport players.

Methodological approaches

Out of the 27 articles, 12 used three-dimensional motion analysis to track passive marker sets. Seven investigations used accelerometers, four used force-sensitive resistors/foot switches, three used inertial measurement units (IMUs), two used instrumented treadmills, and one study used a combination of three-dimensional motion analysis and accelerometers (Schütte et al., 2015). Nineteen studies used motorised treadmills and four were conducted overground, of which three studies used a synthetic track. One study examined non-linear dynamics during overground running on a synthetic track and on a treadmill (Lindsay et al., 2014). Table 2 summarises the methodological approaches taken to record movement data.

Of the studies using motion capture, nine considered positional data of an individual marker or set of markers, including sacrum (Look et al., 2013; Raffalt et al., 2019, 2020; Schütte et al., 2015), head and ankle (Jordan et al., 2009), foot and pelvis (Dingwell et al., 2018), cervical spine (Mehdizadeh et al., 2014), ankle (Mehdizadeh et al., 2016), and right heel (Mo & Chow, 2018). Four studies considered joint angles, of which two restricted analysis to the sagittal angles, looking at flexion/extension of the hip and knee (Look et al., 2013), and hip, knee, and ankle (Raffalt et al., 2020), one considered sagittal and frontal planes at the hip, knee, and ankle (Estep et al., 2018), and one considered movements in all three planes at the hip, knee, and ankle (Hunter et al., 2021). Accelerometers varied in placement, with six studies using only one unit to record movement. Of these, three studies examined dynamics of the lumbar spine (McGregor et al., 2009; Parshad et al., 2012; Schütte et al., 2015, 2018), one study used accelerometers placed on the foot (Lindsay et al., 2014), and one study positioned the accelerometer on the tibia (Meardon et al., 2011). Further studies used a combination of accelerometers in different positions, including foot, pelvis, and thorax (Hoenig et al., 2019), tibia and sacrum (Murray et al., 2017), cervical vertebrae 7, pelvis, wrist, and ankle (Rabuffetti et al., 2019), and lumbar spine and tibia (Schütte et al., 2018). Capture frequencies varied greatly for each method of data collection, with motion capture (100–250 Hz) and IMU (100–256 Hz) sampling rates generally lowest. Studies that utilised accelerometery (124–2000 Hz) and force sensitive resistors (247–2000 Hz) used a wide range of frequencies, and both studies using the instrumented treadmill chose a sampling rate of 250 Hz.

A variety of methods were used to standardise running speed between participants. The most common approach used by studies for analysis was the preferred or self-selected speed. Seven of the included studies used either one fixed speed or a combination of different fixed speeds. Of these studies, only one gave a rationale for choosing the speed (Strongman & Morrison, 2021). Additionally, to explore non-linear dynamics over a range of speeds, three studies used a graded exercise test (McGregor et al., 2009; Murray et al., 2017; Parshad et al., 2012). Some studies used physiological thresholds to determine running speed including anaerobic threshold (Mo & Chow, 2018), critical speed (Hunter et al., 2021), and percentage of $\dot{V}O_{2max}$ (Hollander et al., 2021). Four studies examined movement dynamics using a time trial: two completing a run at 5 km pace (Hoenig et al., 2019; Meardon et al., 2011) and two completing the run in a 3.2 km time trial (Schütte et al., 2015, 2018). One study explored movement dynamics using walk-run or run-walk transitions (Jordan et al., 2009). Froude number-based speeds were used in two studies (Dingwell et al., 2018; Strongman & Morrison, 2021). Strongman and Morrison (2021) used a combination of Froude number,

Table 1. Basic sample characteristics of included studies.

Study	Location	Sample	Participants, M/F	Mass (kg)	Stature (m)	Age (years)
Dingwell et al. (2018)	USA	Total $n = 10$Recreational runners $n = 10$ Recreational runners $n = 10$	5/5	68.9 ± 12.0	1.75 ± 0.11	24.6 ± 2.0
Estep et al. (2018)	USA	Total $n = 17$Recreational runners $n = 15$Competitive runners $n = 2$ Recreational runners $n = 15$ Competitive runners $n = 2$	12/5	82.5 ± 23.7 NR NR	1.75 ± 0.09 NR NR	38.0 ± 11.6 NR NR
Fuller et al. (2016)	Australia	Total $n = 26$Trained runners $n = 26$ Trained runners $n = 26$	26/0	61.7–88.2	1.69–1.90	18–40
Fuller et al. (2017)	Australia	Total $n = 10$Trained runners $n = 10$ Trained runners $n = 10$	10/0	76.0 ± 6.0	NR	36.0 ± 8.0
Hoenig et al. (2019)	Germany	Total $n = 30$Recreational runners $n = 15$Competitive runners $n = 15$ Recreational runners $n = 15$ Competitive runners $n = 15$	30/0	NR NR NR	NR NR NR	NR 25.3 ± 7.6 28.7 ± 4.3
Hollander et al. (2021)	Germany	Total $n = 41$Level of fitness/training status not given Level of fitness/training status not given	20/21	71.3 ± 11.5	1.78 ± 0.08	25.2 ± 3.2
Hunter et al. (2021)	UK	Total $n = 10$Recreational runners $n = 10$ Recreational runners $n = 10$	10/0	72.1 ± 9.6	1.76 ± 0.04	29.3 ± 10.1
Jordan et al. (2006)	USA	Total $n = 8$Recreational runners $n = 8$ Recreational runners $n = 8$	0/8	57.8 ± 3.6	1.64 ± 0.02	24.9 ± 2.0
Jordan et al. (2007)	USA	Total $n = 11$Recreational runners $n = 11$ Recreational runners $n = 11$	0/11	57.7 ± 3.6	1.65 ± 0.04	24.5 ± 1.8
Jordan et al. (2009)	USA	Total $n = 12$Recreational runners $n = 12$ Recreational runners $n = 12$	0/12	62.4 ± 5.6	1.67 ± 0.03	26.2 ± 2.9
Lindsay et al. (2014)	South Africa	Total $n = 9$Trained runners $n = 9$ Trained runners $n = 9$	9/0	70.2 ± 8.5	1.76 ± 0.05	27.8 ± 6.8
Look et al. (2013)	USA	Total $n = 17$Runners without amputation $n = 11$Runners with transtibial amputation $n = 6$ Runners without amputation $n = 11$ Runners with transtibial amputation $n = 6$	12/58/34/2 8/3 4/2	NR	NR	NR
Mann et al. (2015)	Luxembourg	Total $n = 90$Runners with running-related injury $n = 44$Control group $n = 46$Level not specified Runners with running-related injury $n = 44$ Control group $n = 46$ Level not specified	NR33/1133/13 33/11 33/13	NR 70.0 ± 9.0 73.0 ± 9.0	NR 1.76 ± 0.08 1.77 ± 0.07	NR 40.0 ± 10.0 42.0 ± 8.0
McGregor et al. (2009)	USA	Total $n = 7$Trained runners $n = 7$ Trained runners $n = 7$	7/0	65.5 ± 5.7	1.81 ± 0.04	21.4 ± 1.7
Meardon et al. (2011)	USA	Total $n = 18$Recreational runners with prior injury $n = 9$Recreational runners without prior injury $n = 9$ Recreational runners with prior injury $n = 9$ Recreational runners without prior injury $n = 9$	NRNRNR NR NR	NR 66.3 ± 7.8 62.6 ± 8.3	NR 1.71 ± 9.3 1.70 ± 10.9	NR 29.3 ± 10.3 25.9 ± 8.5
Mehdizadeh et al. (2014)	Iran	Total $n = 15$Level of fitness/training status not given Level of fitness/training status not given	15/0	68.8 ± 3.9	1.76 ± 0.04	24.1 ± 1.0
Mehdizadeh et al. (2016)	Iran	Total $n = 10$National-level football players $n = 10$ National-level football players $n = 10$	10/0	71.6 ± 4.8	1.79 ± 0.04	23.2 ± 2.9
Mo and Chow (2018)	Hong Kong	Total $n = 34$Novice runners $n = 17$Experienced runners $n = 17$ Novice runners $n = 17$ Experienced runners $n = 17$	29/515/214/3 15/2 14/3	NR 62.8 ± 10.4 63.4 ± 9.5	NR 1.73 ± 0.08 1.70 ± 0.06	NR 23.8 ± 4.7 24.9 ± 6.4
Murray et al. (2017)	Qatar	Total $n = 6$National level runners $n = 6$ National level runners $n = 6$	6/0	51.0 ± 5.8	1.69 ± 0.09	15.6 ± 1.2
Nakayama et al. (2010)	Japan	Total $n = 14$Trained runners $n = 7$Non-runners $n = 7$ Trained runners $n = 7$ Non-runners $n = 7$	14/07/07/0 7/0 7/0	NR 58.0 ± 7.0 68.4 ± 7.1	NR 1.70 ± 0.06 1.73 ± 0.05	NR 23.9 ± 1.9 23.9 ± 0.7
Parshad et al. (2012)	USA	Total $n = 14$Trained runners $n = 7$Untrained runners $n = 7$ Trained runners $n = 7$ Untrained runners $n = 7$	14/07/07/0 7/0 7/0	NR 65.5 ± 5.7 69.9 ± 11.8	NR 1.81 ± 0.04 1.77 ± 0.05	NR 21.4 ± 1.7 31.6 ± 9.5
Rabuffetti et al. (2019)	Italy	Total $n = 25$Level of fitness/training status not given Level of fitness/training status not given	14/11	64.1 ± 13.6	1.72 ± 0.09	26.3 ± 4.5
Raffalt et al. (2019)	USA	Total $n = 10$Physically active $n = 10$ Physically active $n = 10$	5/5	73.4 ± 14.3	1.75 ± 0.10	22.7 ± 3.6
Raffalt et al. (2020)	USA	Total $n = 11$Physically active $n = 11$ Physically active $n = 11$	5/6	72.1 ± 14.3	1.74 ± 0.10	23.3 ± 3.9
Schütte et al. (2015)	Belgium	Total $n = 20$Runners with varying degrees of experience $n = 20$ Runners with varying degrees of experience $n = 20$	12/8	66.1 ± 6.2	1.77 ± 0.08	21.1 ± 2.1
Schütte et al. (2018)	Belgium	Total $n = 30$Recreational runners with history of medial tibial stress syndrome $n = 14$Recreational runners without history of medial tibial stress syndrome $n = 16$ Recreational runners with history of medial tibial stress syndrome $n = 14$ Recreational runners without history of medial tibial stress syndrome $n = 16$	18/128/610/6 8/6 10/6	NR 68.3 ± 9.0 63.1 ± 9.5	NR 1.77 ± 0.10 1.75 ± 0.07	NR 20.4 ± 0.8 20.1 ± 0.7
Strongman and Morrison (2021)	UK	Total $n = 16$Recreationally active $n = 10$ Recreationally active $n = 10$	7/9	67.0 ± 14.8	1.72 ± 0.10	23.0 ± 3.5

Note: Body mass, stature, and age values are reported as Mean ± SD; NR, not reported.

Table 2. Methodological characteristics of studies included in analysis and summary of key findings.

Study	Surface	Task	Data collection method	Outcome measures	Analysis	Main findings
Dingwell et al. (2018)	Treadmill	Walk at predicted comfortable speed and transition speed 4 min: 1.2 m·s^{-1} 2.2 m·s^{-1} Run at predicted comfortable speed and transition speed 4 min: 2.2 m·s^{-1} 2.8 m·s^{-1}	Motion capture 120 Hz	Stride length Stride time Stride speed	DFA-α	No main effect for speed.
Estep et al. (2018)	Treadmill	Walk at self-selected speed 5 min: 1.39 m·s^{-1} Run at self-selected speed 5 min: 2.56 m·s^{-1}	Motion capture 200 Hz	Joint angles: Ankle plantar/ dorsi flexion Knee flexion/ extension, Knee abduction/ adduction Hip flexion/ extension Hip abduction/ adduction	ApEn	ApEn lower in the walking condition when compared to running for knee flexion/extension, knee abduction/adduction, hip flexion/ extension, and hip abduction/ adduction.
Fuller et al. (2016)	Treadmill	Run for 5 min in a conventional shoe and minimalist shoe at: 3.06 m·s^{-1} 3.61 m·s^{-1} 4.17 m·s^{-1}	Force-sensitive resistors 2000 Hz	Stride interval	DFA-α	No main effect for speed.
Fuller et al. (2017)	Treadmill	Run for 5 min at baseline, overreached state, and recovered state at: 2.22 m·s^{-1} 2.92 m·s^{-1} 3.61 m·s^{-1}	Force-sensitive resistors 2000 Hz	Stride interval	DFA-α	No main effect for speed. No main effect of the overreaching protocol on stride interval long-range correlations.
Hoenig et al. (2019)	Overground Synthetic Track	5 km time trial: Average vel. (rec): 3.35 m·s^{-1} Average vel. (comp): 4.54 m·s^{-1}	IMU 100 Hz	Angular velocity of the sensors at thorax, pelvis, and foot	LyE	Lelvis sensor speed decreased during the run in both recreational and competitive runners.
Hollander et al. (2021)	Treadmill	Run for 15 min at: 70% $\dot{V}O_{2max}$ Speed not reported	IMU 256 Hz	Angular velocity of tibia	LyE	LyE measured at the tibia increased over the course of the 15 min run.
Hunter et al. (2021)	Treadmill	Run for 20 min or until task failure at: 3.71 m·s^{-1} 3.94 m·s^{-1} 4.21 m·s^{-1} 4.64 m·s^{-1}	Motion capture 200 Hz	Sagittal, frontal, and transverse joint rotations at the hip, knee, and ankle	SampEn DFA-α	Changes to kinematic complexity over time were consistent between heavy and severe intensity domains during running. DFA-α reduced and SampEn increased when running at 4.64 m·s^{-1}
Jordan et al. (2006)	Treadmill	Run for 8 min at: 80% PRS 90% PRS 100% PRS 110% PRS 120% PRS PRS: 3.03 m·s^{-1}	Instrumented treadmill 250 Hz	Stride interval	DFA-α	DFA-α followed a quasi-U-shaped function, with the minimum at the preferred running speed.
Jordan et al. (2007)	Treadmill	Run for 8 min at: 80% PRS 90% PRS 100% PRS 110% PRS 120% PRS PRS not reported	Instrumented treadmill 250 Hz	Stride interval Stride length Step interval Step lengt Vertical impulse Duration of contact Peak vGRF Time to active peak vGRF	DFA-α	DFA-α followed a quasi-U-shaped function, with the minimum at the preferred running speed.
Jordan et al. (2009)	Treadmill	Locomoting for 5 min at:90, 95, 97.5, 100, 102.5, 105, and 110% of the W – R transition speed 90, 95, 97.5, 100, 102.5, 105, and 110% of the R – W transition speed W – R transition: 1.97 m·s^{-1} R – W transition: 1.92 m·s^{-1}	Motion capture 125 Hz	Stride interval Ankle marker trajectory Head marker trajectory	DFA-α LyE	LyE and DFA-α of ankle and head decreased with increasing speeds, with a minima evident around preferred running speed

(*Continued*)

Table 2. (Continued).

Study	Surface	Task	Data collection method	Outcome measures	Analysis	Main findings
Lindsay et al. (2014)	Treadmill Overground Synthetic Track	Run for 8 min at: 80% PRS 90% PRS 100% PRS 110% PRS 120% PRS PRS not reported	Accelerometery 2000 Hz	Stride interval	DFA-α PSD MSE	No main effect for speed. Higher DFA-α and PSD scaling exponent, as well as lower MSE in treadmill running compared to overground.
Look et al. (2013)	Treadmill	Run for > 10 strides at 3 m·s^{-1}. Speed increased by 1 m·s^{-1} until participants reported approaching top speed.	Motion capture 300 Hz	Sacral marker position: Vertical axis Mediolateral axis Anteroposterior axis Sagittal plane knee- and hip-joint angles	LyE	LyE of centre of mass, knee, and hip dynamics increased as run speed increased.
Mann et al. (2015)	Treadmill	Run for 2 min at: 80% PRS 90% PRS 100% PRS 110% PRS 120% PRS Control group PRS: 2.92 m·s^{-1} Previously inured runners PRS: 3.00 m·s^{-1}	Force-sensitive resistors 247 Hz	Strike index Contact time Flight time Stride time	DFA-α	DFA-α for contact time and stride time decreased with increasing speeds.
McGregor et al. (2009)	Treadmill	Incremental exercise test to task failure. Started at 0.56 m·s^{-1} and speed increased by 0.56 m·s^{-1} every 2 min. Average speed of 6.14 m·s^{-1} at task failure	Accelerometery 625 Hz	Accelerations at lumbar spine in: Vertical direction Mediolateral direction Anteroposterior direction	CE	In all directions, CE of accelerations was lower at task failure relative to the first running stage.
Meardon et al. (2011)	Overground Synthetic Track	Run at self-reported 5 km pace until task failure. Average speed no injury 3.49 m·s^{-1} Average speed injury 3.48 m·s^{-1} Pooled average distance: 5,700 ± 900 m	Accelerometery 1000 Hz	Stride time	DFA-α	A significant linear trend evident with a reduction in DFA-α over the course of the run
Mehdizadeh et al. (2014)	Treadmill	Forwards and backwards running for 2 min at: 80% PRS 100% PRS 120% PRS PRS not reported	Motion capture 100 Hz	Velocity of the C7 marker in: Vertical direction Mediolateral direction Anteroposterior direction	Short-term LyE Long-term LyE	Short term LyE of the C7 marker in all directions increased linearly with speed Long-term LyE of the C7 marker showed no significant difference between speeds
Mehdizadeh et al. (2016)	Treadmill	Forward, backward, and lateral running for 2 min at: 80% PRS 100% PRS 120% PRS Forward PRS: 2.30 m·s^{-1} Backward PRS: 1.26 m·s^{-1} Lateral PRS: 1.28 m·s^{-1}	Motion capture 100 Hz	Speed of the ankle marker in: Mediolateral direction Anteroposterior direction	LyE maxFM	Different speeds did not significantly change local (LyE) and orbital (maxFM) dynamic stabilities in any direction of running.
Mo and Chow (2018)	Treadmill	Run at anaerobic threshold speed for 31 min Experienced runners: 3.5 m·s^{-1} Novice runners: 3.08 m·s^{-1}	Motion capture 200 Hz	Stride interval	DFA-α	Significant effect of time, with DFA-α changed with time in a roughly U-shaped trend Significant group x time interaction for experienced and novice runners, with novice runners exhibiting decreased DFA-α when compared to experience runners in the last two intervals. No significant group effect.

(*Continued*)

Table 2. (Continued).

Study	Surface	Task	Data collection method	Outcome measures	Analysis	Main findings
Murray et al. (2017)	Treadmill	Incremental running test consisting of 3 min stages. No speed given.	Accelerometery 148 Hz	Accelerations at trunk and tibia in: Vertical direction Mediolateral direction Anteroposterior direction	SampEn	All variables except SampEn of the VT tibia and AP waist accelerations showed significant positive correlations with blood[La].
Nakayama et al. (2010)	Treadmill	Run for 10 min at: 80% PRS 100% PRS 120% PRS Trained runners PRS: 2.97 m·s^{-1} Non-runner PRS: 2.44 m·s^{-1}	Force-sensitive resistors 1000 Hz	Stride interval	DFA-α	No significant main effect for speed or training status.
Parshad et al. (2012)	Treadmill	Incremental exercise test to task failure. Started at 0.56 m·s^{-1} and speed increased by 0.56 m·s^{-1} every 2 min. Speed at task failure not given.	Accelerometery 617 Hz	Accelerations at lumbar spine in: Vertical direction Mediolateral direction Anteroposterior direction	CE	No significant change as a result of speed in either group. In all axes, CE was lower at exhaustion relative to the first running stage for untrained runners. For trained runners, CE decreased over the course of the run in V and ML directions but increased in AP direction.
Rabuffetti et al. (2019)	Treadmill	Walk for minimum of 100 s at: 1.0 m·s^{-1} 1.4 m·s^{-1} 1.8 m·s^{-1} Run for minimum of 100 s at: 1.8 m·s^{-1} 2.2 m·s^{-1}	IMU 140 Hz	Accelerations at C7, pelvic, and wrist in: Vertical direction Mediolateral direction Anteroposterior direction	Regularity index Period index	No differences between running bouts at 1.8 m·s^{-1} and 2.2 m·s^{-1}
Raffalt et al. (2019)	Treadmill	Walk for 3 min at: 1.79 m·s^{-1} 2.46 m·s^{-1} Run for 3 min at: 1.79 m·s^{-1} 2.46 m·s^{-1}	Motion capture 120 Hz	Sacrum marker displacement in: Vertical direction Mediolateral direction Anteroposterior direction	LyE	No difference in LyE in either algorithm between different running speeds.
Raffalt et al. (2020)	Treadmill	Walk for 3 min at: 0.89, 1.12, 1.34, 1.56, 1.79, 2.01, 2.24 and 2.46 m·s^{-1} Run for 3 min at: 1.79, 2.01, 2.24, 2.46, 2.68, 2.91, 3.13 and 3.35 m·s^{-1}	Motion capture 120 Hz	Hip, knee, and ankle joint angles in the sagittal plane Sacrum marker displacement in: Vertical direction Mediolateral direction Anteroposterior direction	CoD LyE	During running, the LyE and CoD of all three joints decreased significantly in a curvilinear fashion with increasing speed No significant relationship between speed and LyE and CoD of the centre of mass during running.
Schütte et al. (2015)	Treadmill	Run to task failure at speeds equivalent to 3.2 km time trial performance (3.89 m·s^{-1})	Accelerometery 400 Hz Motion capture 150 Hz	Sacrum marker displacement in: Vertical direction Mediolateral direction Anteroposterior direction Accelerations at lumbar spine in: Vertical direction Mediolateral direction Anteroposterior direction Stride interval Step interval	SampEn Unbiased autocorrelation coefficient	Step regularity decreased in the AP direction in the fatigued state. SampEn of AP accelerations decreased in the fatigued state.

(*Continued*)

Table 2. (Continued).

Study	Surface	Task	Data collection method	Outcome measures	Analysis	Main findings
Schütte et al. (2018)	Overground Synthetic Track	Continuous maximal effort fatiguing run of 3200 m Control: 3.91 m·s^{-1} Previously injured: 3.77 m·s^{-1}	Accelerometery 1024 Hz	Accelerations at lumbar spine and tibia in: Vertical direction Mediolateral direction Anteroposterior direction	SampEn Unbiased autocorrelation coefficient	No significant differences between beginning and end of fatiguing run in the control group.
Strongman and Morrison (2021)	Treadmill	Fixed speed: 2.94 m·s^{-1} Froude speed: 2.94 m·s^{-1} Self-selected speed: 2.28 m·s^{-1} And runs 10% higher and lower in each case	Motion capture 250 Hz	Joint angles for sagittal movements of the hip and knee	sampEn LyE	No statistically significant differences were found between speeds.

PRS: preferred running speed; SampEn: sample entropy; DFA-α: detrended fluctuation analysis exponent; LyE: lyapunov exponent; PSD: power spectral density; CE: control entropy; MSE: multiscale entropy; CoD: correlational dimension; maxFM: maximum Floquet multiplier; GRF: ground reaction force. Where more than one method of data collection and outcome measure was used, only methods which resulted in data analysis using non-linear methods are presented.

fixed speed, and self-selected speeds to evaluate how speed affects non-linear dynamics during running. Table 2 summarises the effects of speed or fatigue on non-linear dynamics during running tasks in the included studies.

Discussion

The aim of this scoping review was to evaluate the approaches taken to quantify changes to non-linear movement dynamics in response to fatigue, different running speeds, or fitness levels. Herein, changes to movement dynamics, as measured by non-linear methods, are summarised and discussed.

Effects of running speed

Researchers reporting DFA-α values have demonstrated inconsistent findings when examining the effects of speed. Several studies concluded no significant differences in DFA in response to increasing running speed (Dingwell et al., 2018; Fuller et al., 2016, 2017; Jordan et al., 2009; Lindsay et al., 2014; Nakayama et al., 2010). However, more pronounced changes to DFA-α, when speed is manipulated, are evident at speeds at or close to (±20%) the preferred running speed. Typically, the lowest DFA-α value is observed near the preferred running speed, and it increases when speed is decreased or increased in a quasi-U-shape (Jordan et al., 2006, 2007; Mann et al., 2015). A decrease in DFA-α at greater running speeds was observed in the single study considering joint kinematics (Hunter et al., 2021). However, this approach has been disputed, arguing joint angle time series lacks relative roughness for appropriate use of DFA (Marmelat et al., 2012). Changes to statistical persistence of movement in response to changes in speed may be more pronounced around the preferred running speed (Jordan et al., 2006, 2007; Mann et al., 2015) or at much greater speeds (Hunter et al., 2021). This may be due to the dynamics of running at preferred running speed or at slower speeds being considered more stable than that of non-preferred speeds or much greater speeds. It can be argued that running at the preferred or slower speeds may increase the number of dynamical degrees of freedom, increasing the number of viable solutions to navigate the environment, resulting in a greater number of interstride variability.

When considering measures of entropy, Estep et al. (2018) demonstrated greater randomness of hip and knee movement during running when compared to walking. Correspondingly, Hunter et al. (2021) demonstrated decreased regularity of sagittal hip angles at 115% critical speed when compared to slower speeds. However, reduced complexity of accelerometery values, as evidenced by decreased control entropy values, has been shown at greater running speeds throughout an incremental treadmill run (McGregor et al., 2009; Parshad et al., 2012). It was posited that this could be due to the emergence of greater constraints at higher speeds, including greater metabolic demand, changes to elastic and spring characteristics, and changes to joint coordination patterns (Saibene & Minetti, 2003; Sasaki & Neptune, 2006). Furthermore, Rabuffetti et al. (2019) demonstrated a ceiling effect for regularity of accelerations during the two chosen running speeds, whereby increasing running speed from 1.8 m·s^{-1} to 2.2 m·s^{-1} did not result in further changes to regularity as it reached its maximum. When examining multiscale entropy of stride time series, Lindsay et al. (2014) found no changes with increasing speed. Similarly, when considering sample entropy of hip and knee joint angles, no differences were shown between different running speeds (Strongman & Morrison, 2021). Moreover, a similar pattern emerged for the LyE, with no significant differences between speeds (Strongman & Morrison, 2021).

Further to the findings of Strongman and Morrison (2021), research has demonstrated conflicting findings regarding the effect of speed on measures of local dynamic stability. During shorter trials of at least 8 strides, Look et al. (2013) found that the LyE of a sacral marker, and sagittal knee and hip joint angles all increased with an increase of treadmill speed in a graded exercise test. However, as time series were not normalised, the series is likely to have contained a different number of data points per stride, which may affect LyE values (England & Granata, 2007; Stenum et al., 2014). When considering how local dynamic stability changes over a range of speeds, Raffalt et al. (2020) demonstrated no significant relationship between speed and LyE and correlational dimension of a sacral marker. There was a significant curvilinear relationship of LyE and correlational dimension of sagittal angles of the hip, knee, and ankle, decreasing significantly in a curvilinear fashion with increasing speeds from 1.79 m·s^{-1} to 3.35 m·s^{-1}. The researchers, therefore, questioned the use of the centre of mass when evaluating movement dynamics. However, other researchers have utilised a sacral marker to demonstrate changes to centre of mass dynamics (Look et al., 2013; Mehdizadeh et al., 2014). When considering forwards and backwards running, Mehdizadeh et al. (2014) demonstrated a weak significant linear relationship between short-term LyE of a cervical spine marker and speed. As running speed increased, short-term LyE also increased, suggesting that a single neuromuscular mechanism may be responsible for control of movement in both directions. However, in a follow-up investigation involving lateral, backwards, and forwards running, no differences in local dynamic stability of an ankle marker were noted when speed was increased (Mehdizadeh et al., 2016). Interestingly, stability was greater in the secondary plane of progression for every direction, suggesting that a greater active control is required to maintain stability. As different markers were used for the studies, a definitive conclusion on the effects of running speed in different directions, and therefore what modulates active control in the plane perpendicular to progression, is not possible.

Further to differences in the type of time series analysed, inconsistent findings may also be due to differences in normalisation procedure, time series length, and the methods used to reconstruct the state space. However, when comparing different algorithms and normalisation procedures, there was no difference in local dynamic stability of a sacral marker between running at 1.79 m·s^{-1} when compared to a preferred running speed of 2.46 m·s^{-1} (Raffalt et al., 2019). The researchers were able to differentiate the local dynamic stability between walking and running trials. Furthermore, Raffalt et al. (2019) demonstrated that the effectiveness of both Wolf et al. (1985) and Rosenstein et al. (1993) algorithms improved using individual time delay and embedding dimension for each variable and each trial, rather than using a group average. However, this approach may result in different topographies of the state space reconstruction, rendering it inappropriate for repeated measures designs with multiple visits (van Schooten et al., 2013).

It is unclear why there may be changes to non-linear movement dynamics at different running speeds. However, researchers have posited that changes to movement dynamics during running at greater speeds may be a protective mechanism, rendering the body more adaptable to perturbations (Estep et al., 2018; Hunter et al., 2021). While evidence for this is limited, studies investigating injured populations have demonstrated more random movement when compared to healthy controls (Mann et al., 2015; Meardon et al., 2011). Conversely, it has been shown that during running, runners with medial tibial stress syndrome exhibit different dynamics to healthy controls, showing a reduction in complexity, evidenced by decreases in SampEn (Schütte et al., 2018). It may be that there is a loss of motor control at greater speeds, and therefore a compromise is made between movement speed and movement accuracy. If true, this, due to a diminished ability to navigate the environment with sufficient control, would render runners more likely to be injured at greater speeds. Furthermore, running at higher speeds is associated with a greater degree of head movement, which is likely to affect visuo-vestibular feedback (Paillard, 2012). Future studies should consider whether altered movement dynamics are beneficial or detrimental to injury risk. Further lines of inquiry may also assess the ability to successfully overcome perturbations in groups that exhibit more random, or more regular, movement patterns.

There are a variety of methods used to standardise running speed, the most common being the use of self-selected speeds. The use of self-selected speeds enables researchers to assess differences between a more stable attractor, i.e., preferred running speed, when compared to unstable movements (i.e., speeds below or above the preferred running speed). Briefly, a stable attractor is a system where there is a high probability of specific patterns reoccurring in a particular order (i.e., lower complexity and variability) (Raffalt et al., 2020). However, the use of self-selected speeds has substantial limitations including the lack of standardised protocol, a potential for research bias (Brinkerhoff et al., 2022), and a highly subjective nature of what is considered comfortable (Plotnik et al., 2015). Due to a greater dynamic similarity by scaling to anthropometry, i.e., leg length, it has been suggested that using Froude speed results in less variable non-linear measures across participants when compared to fixed or self-selected speeds (Strongman & Morrison, 2021). However, this was investigated in a small sample size ($n = 16$) and a small range of speeds (±10%).

The use of assigning speeds based on exercise intensity domains may be a useful framework, enabling homogenous physiological responses to examine subsequent movement dynamics (Meyler et al., 2021). However, this approach assumes that changes to movement dynamics are driven by physiological responses to exercise at different intensities. Studies which have examined movement dynamics near to physiological thresholds have not provided conclusive results (Hollander et al., 2021; Hunter et al., 2021; Mo & Chow, 2018). Further research should seek to expound this relationship further. Finally, the use of graded exercise tests to assess movement dynamics has been used to test a range of speeds while minimising participant burden (McGregor et al., 2009; Murray et al., 2017; Parshad et al., 2012). Nonetheless, this approach may be limited as changes in the latter stages of the test may be affected by accumulated fatigue rather than increased running speed. However, the effects of fatigue on non-linear measures are conflicting. In summary, changes to movement dynamics from altered running speed are not consistent between studies. However, DFA-α and correlational dimension appear to reach a minimum at preferred running speed and increased in response to much greater increases or decreases in speed. Measures of stability tended to show a decrease in stability with faster running speeds. However, measures of entropy may not be sufficiently sensitive to minor changes in running speed, with significant changes only noted once running speed was changed markedly.

Effects of fatigue

When considering the relationship between fatigue and non-linear measures, many studies did not directly measure markers of fatigue, instead relying on non-invasive measures including ratings of perceived exertion (RPE) and heart rate (HR). This is arguably an important limitation of the findings in this area. However, given the known physiological responses within the three intensity domains, it is possible to infer the intensity at which some of the exercise is performed. Briefly, exercise below the severe intensity domain, i.e., within the heavy or moderate intensity domains, is associated with the achievement of a steady state in physiological responses including oxygen consumption ($\dot{V}O_2$) and intramuscular concentration of metabolites. However, within the severe intensity domain, a steady state of $\dot{V}O_2$ and HR is not possible, and concentrations of fatigue related metabolites reaching a critical threshold eventually results in the termination of exercise (Poole et al., 2016). For example, Meardon et al. (2011) showed DFA-α reduced at the end of a prolonged run at 5-km race pace, where participants achieved an average 97% of their maximum HR, suggesting a severe domain exercise intensity. Similarly, participants during a time trial at 5-km race pace were likely performing in the severe intensity domain, with end run RPE values of 18.7 ± 1.0 and 18.9 ± 0.8, and end-run blood [lactate] ([La]) of 6.3 ± 1.9 mmol/L and 8.3 ± 2.2 mmol/L, for recreational and competitive runners, respectively (Hoenig et al., 2019). Local dynamic stability increased during the run in both groups from the first 500 m to the last 500 m of the 5 km time trial at the pelvis ($P = 0.001$, $\eta_p^2 = 0.268$) and thorax ($P = 0.004$, $\eta_p^2 = 0.181$). In comparison, Hollander and colleagues (2021) demonstrated a 0.579 increase in LyE, denoting a decrease in running stability, measured at the tibia over the course of a 15-min run performed at 70% of the speed evoking maximum $\dot{V}O_{2max}$ may require less attention and therefore spare cognitive resources to keep the runner stable when compared to a 5000 m run.

Mo and Chow (2018) showed an effect for time during a 31-min run with DFA decreasing in the middle of the run before increasing towards the end of the run at a speed corresponding to the first ventilatory threshold i.e., the boundary between moderate and heavy intensity exercise domains. This coincided with end run blood [La] of 8.0 ± 2.0 mmol/L and 7.4 ± 1.5 mmol/L, and end run RPE of 17.5 ± 0.9 (intensity = "very hard") and 18.3 ± 0.9 (intensity = "extremely hard"), for experienced and novice runners, respectively. The values at the completion of the run correspond with what could be expected at the higher end of the heavy intensity or the lower end of the severe intensity domain, suggesting that the runs were performed at a much greater intensity than intended. Similar RPE (all greater than 17) were noted at the end of an exhaustive treadmill protocol performed at 3.2 km time trial pace (Schütte et al., 2015). It was found that step regularity increased alongside decreased sample entropy of trunk accelerations, indicating lesser randomness, in the fatigued state (Schütte et al., 2015). In a follow-up study, step regularity was shown to decrease over the course of a 3.2 km time trial accompanied with an RPE of 19.44 ± 0.63 (Schütte et al., 2018). These findings suggest that fatigue mechanisms, particularly those associated with the severe intensity domain, show variable effects on non-linear dynamics. The differences in findings may be due to different parameters being evaluated. To explore the effects of different fatigue mechanisms, Hunter et al. (2021) sought to examine changes to fractal scaling and regularity of joint angles in the heavy and severe intensity domains. Despite significant differences in $\dot{V}O_2$ and blood [La] between the trials performed at different intensity domains ($P < 0.05$), no significant differences were evident over time, contradicting the notion that physiological responses are responsible for mediating changes to non-linear movement dynamics. However, participants ran at speeds close to the boundary between heavy and severe domains, i.e., the critical speed. There is recent evidence to suggest that the domains are separated by a phase transition rather than by a sudden threshold (Pethick et al., 2020), and so more marked differences in movement dynamics could be expected further from the critical speed.

The changes in movement dynamics caused by fatigue in these studies may be caused by metabolite accumulation associated with higher intensity exercise (Mello et al., 2010). Metabolites associated with peripheral fatigue exert inhibitory effects on a-motor neurons through activation of group III and IV muscles afferents (Amann et al., 2020). As a result, neural activation of locomotor muscle, and therefore motor output accuracy, may be diminished, resulting in compromised motor control (Paillard, 2012) and therefore changes to movement dynamics. Indeed, a reduction in the complexity of force production has been shown exclusively within the severe intensity domain (Pethick et al., 2015, 2016). Furthermore, in the one study seeking to examine the effects of fatigue induced by an overreaching protocol, no differences in scaling exponent of stride intervals were demonstrated, despite a significant decrease ($P < 0.01$) in time trial performance (Fuller et al., 2017). The conflicting findings regarding changes to movement dynamics over time during whole body movement indicate that not a single mechanism, e.g., peripheral fatigue, is responsible for these changes. Inconsistent findings may also be due to different levels of participant fitness levels. Future studies examining full body movement may wish to include more direct measures of fatigue, i.e., measures of voluntary activation or electrical stimulation methods, to strengthen conclusions, and to validate the exercise intensity prescribed.

Effects of fitness levels

Four studies considered whether the level of fitness affected non-linear running dynamics (Hoenig et al., 2019; Mo & Chow, 2018;

Nakayama et al., 2010; Parshad et al., 2012). Three of these (Hoenig et al., 2019; Mo & Chow, 2018; Parshad et al., 2012) identified significant group differences in movement dynamics ($P < 0.05$). Hoenig et al. (2019) demonstrated lower levels of local dynamic foot stability in recreational runners when compared to competitive runners throughout a 5000-m run. This finding suggests that higher level runners may have greater control of stability, which may be explained by an enhanced ability to explore greater degrees of freedom to navigate environments. Indeed, Parshad and colleagues (2012) showed greater control entropy in trained, when compared to untrained, runners. The researchers further suggested lower constraints, e.g., lower metabolic demands, to enable experienced runners to run faster. Similarly, Nakayama et al. (2010) identified "a significant tendency of the main effect of training" ($p = 0.055$), showing smaller long-term correlations for trained runners. However, Mo and Chow (2018) found a significant group × time interaction for experienced and novice runners in a 31-min run at the intensity corresponding to the anaerobic threshold, with novice runners exhibiting decreased DFA-α when compared to experience runners in the last two intervals. The findings suggest that runners adopt different gait strategies as fatigue progresses, with novice runners exhibiting more random fluctuations. These findings are in vast contrast to findings that demonstrated more random fluctuations in trained runners when running in a non-fatigued state (Nakayama et al., 2010). Running in a non-fatigued state may render runners more able to exhibit greater independence of each stride interval and increased degrees of freedom. These increased degrees of freedom may have been utilised by non-runners in the study of Mo and Chow (2018) during prolonged running or when experiencing fatigue as a protective mechanism to render the runner more adaptable. It is also worth noting that different speeds were used for each study, which may limit pooled conclusions. Further research should expound the relationship between training status and non-linear movement dynamics, especially when considering the role of cognition in controlling these parameters.

Given movement dynamics may be mediated by running speed, it could be posited that differences between training status of runners may be due to different running speeds. Indeed, neither Hoenig et al. (2019) nor Mo and Chow (2018) considered different running speeds within the statistical analysis as a covariate. Therefore, findings should be treated with caution. Nonetheless, Hoenig et al. (2019) time-normalised the time series analysed to 100 data points per stride and used a consistent number of strides before calculating the LyE, likely mitigating differences due to speed. Moreover, similar findings were evident when including speed as a covariate (Nakayama et al., 2010) and when comparing between same speeds in a graded exercise test (Parshad et al., 2012). Training status was usually based on self-reported training experience rather than measures of cardiorespiratory fitness. However, differences between groups were evident in performance measures including preferred running speed (Nakayama et al., 2010), anaerobic threshold speed (Mo & Chow, 2018), or $\dot{V}''O_{2max}$ (Parshad et al., 2012). Hoenig et al. (2019) defined recreational or competitive runners based on recent race performances and age grading criteria, which was subsequently confirmed with $\dot{V}O_{2max}$ and 5 km performance.

In summary, there appears to be an effect of fitness level on non-linear dynamics of movement during running, although caution is warranted due to disparities in methodologies. Trained runners have demonstrated greater local dynamic stability (Hoenig et al., 2019), greater control entropy (Parshad et al., 2012), and greater DFA-α in fatigued states (Mo & Chow, 2018) when compared to either novice runners. These findings suggest that training status has an effect on the regulation of movement dynamics, possibly through reduced task constraints, e.g., reduced effort. In turn, this may improve the runners' ability to maintain stability and a more consistent gait pattern. Future studies should determine whether these changes occur as a result of training, and whether these strategies are beneficial in terms of injury reduction or changes to the energetic cost of running.

Limitations

Current evidence suggests that changes to speed and levels of fatigue may have an impact on movement dynamics when measured using non-linear methods. However, caution is warranted when drawing conclusions from studies which use different methodological approaches to collect data. Inconsistency between data collection methods make deriving a consensus between on the relationship between fatigue, running speed, fitness level, and non-linear measures challenging. Although one study attempted to use multiple sites when using accelerometers and motion capture (Schütte et al., 2015), it remains unclear as to which positions or variables are the most sensitive to changes in speed and fatigue status. Despite most studies using motion capture, the use of accelerometers or pressure sensors provides a promising avenue, through which movement dynamics can be assessed in the field. In addition to different methods utilised to quantify movement dynamics, each applied algorithm is sensitive to parameters used, rendering comparison between studies problematic (Phinyomark et al., 2020; Raffalt et al., 2019; Yentes et al., 2017). The tolerance window, vector length, time series length, and number of scales affect the consistency of each algorithm, and may also lead to conflicting results (Yentes et al., 2013, 2017). Similarly, changes to estimations of the LyE are influenced by the embedding dimension (m) and time delay (τ) parameters that are used when reconstructing the state space (van Schooten et al., 2013), as well as the length of time series and whether it is time normalized (Raffalt et al., 2019). Moreover, differences in variables, e.g., continuous or discrete data (McCamley et al., 2018), and sampling frequency (Raffalt et al., 2019) analysed limit the conclusions and parallels drawn from the body of literature. The relationship between the outputs of each algorithm is not clear; however, there is some evidence to suggest similar findings between entropy and LyE (Stergiou & Decker, 2011b). To this end, authors have suggested that multiple complimentary methods may be used when quantifying movement dynamics (Dierick et al., 2017). A limitation of the body of work is the examination of predominantly male participants. Given males and females exhibit different physiological responses to running (Besson et al., 2022), as well as differences in motor unit behaviour (Lulic-Kuryllo & Inglis, 2022), sexes may exhibit different non-linear movement dynamics when running. We, therefore, encourage more research with female participants to ensure a more balanced representation of both sexes in non-linear dynamics research.

Conclusions

This review has demonstrated that changes to non-linear measures are linked to running speed, fatigue-induced changes, and fitness levels. Conflicting findings were evident when studies examined non-linear features in fatigued states when compared to non-fatigued. Where changes were evident, fatigue tended to result in a more random running pattern. More pronounced alterations to movement dynamics were evident when running speed was either increased or decreased relative to the preferred running speed, forming a curvilinear relationship. Moreover, changes were also evident when more pronounced increases in speed were utilised in studies. Greater fitness levels tended to result in more stable and predictable running patterns, with reduced task constraints evident for well-trained runners. The use of non-linear analyses has also been shown to be sensitive to these variables, although findings are disparate. This can be attributed to differences in (i) experimental design including variables analysed and task, (ii) algorithm used and input parameters, and (iii) the populations studied. However, this review has highlighted the utility of such approaches and adds to the more established body of work where non-linear methods have been applied to injured and disease states. Through refinement and greater consistency in the implementation of the non-linear approaches outlined in this review, underlying mechanisms of motor control during running may be better understood and may be useful in exercise prescription and monitoring. Future research may wish to standardise methods and parameter choices to improve comparison to relevant literature and robustness of findings. Furthermore, this review has highlighted several gaps in the literature which should be addressed to further our understanding of the field.

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