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The application of the Lyapunov Exponent to analyse human performance: A systematic review

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ABSTRACT

Variability is a normal component of human movement, allowing one to adapt to environmental perturbations. It can be analysed from linear or non-linear perspectives. The Lyapunov Exponent (LyE) is a commonly used non-linear technique, which quantifies local dynamic stability. It has been applied primarily to walking gait and appears to be limited application in other movements. Therefore, this systematic review aims to summarise research methodologies applying the LyE to movements, excluding walking gait. Four databases were searched using keywords related to movement variability, dynamic stability, LyE and divergence exponent. Articles written in English, using the LyE to analyse movements, excluding walking gait were included for analysis. 31 papers were included for data extraction. Quality appraisal was conducted and information related to the movement, data capture method, data type, apparatus, sampling rate, body segment/joint, number of strides/steps, state space reconstruction, algorithm, filtering, surrogation and time normalisation were extracted. LyE values were reported in supplementary materials (Appendix 2). Running was the most prevalent non-walking gait movement assessed. Methodologies to calculate the LyE differed in various aspects resulting in different LyE values being generated. Additionally, test-retest reliability, was only conducted in one study, which should be addressed in future.

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Introduction

Movement variability has previously been viewed as measurement noise which should be eliminated (Stergiou et al., 2004). As such successful skill execution was previously characterised by a lack of movement variability, since less variability in outcome measures like error and accuracy represents better performance (Davids et al., 2006). Research has since challenged this notion, positing that a low outcome variability does not necessarily coincide with low technique variability (Preatoni et al., 2013).

Dynamic systems theory (DST) is a human movement theory that corroborates the idea that variability is a functional component of skill, suggesting that movement patterns are created from the collaborative organisation of the neuromuscular system based on the interaction between task (e.g., goals and rules), environmental (e.g., weather, spectators) and organism (individual anthropometry and morphology) constraints (Bernstein, 1967; Davids et al., 2006; Dingwell & Cusumano, 2000; Hamill et al., 1999). Alterations in these constraints may alter movement patterns. DST acknowledges the inherent variability that exists in human movement, recognising that movement variations occur naturally, and allow individuals to adapt to new situations (Davids et al., 2006; Magill & Anderson, 2017; Stergiou & Decker, 2011). For example, individuals alter their walking gait in response to different environmental factors. For example, to compensate for the moving belt of a treadmill, individuals implement a more cautious walking gait by having smaller step lengths and slower self-selected speeds when walking on a treadmill compared to overground walking (Yang & King, 2016). Stergiou and Decker (2011) suggest that a healthy bandwidth of variability exists, where individuals can successfully adapt to novel situations. Beyond this bandwidth, individuals are too variable, resulting in instability, whereas too little variability results in a rigid system, that appears robotic; both of which are unhealthy and do not allow one to successfully manage perturbations.

Variability is also present in sporting movements. For example, basketballers alter their shooting movement pattern to make a basket in response to different environmental factors like the distance from the basket or the presence of defenders (Slegers et al., 2021). Additionally, whether movement variability is desired, depends on the task and its specific context (Davids et al., 2006; Stergiou & Decker, 2011). For example, reducing shoulder joint angular kinematic variability is associated with improved pitch location control in baseball pitching (Glanzer et al., 2021), but in baseball hitting, elite players exhibit

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greater timing variability in their swing than novices to adapt to different pitch types and locations (Gray, 2020).

However, how variability is quantified influences the interpretation of the results. Variability has typically been quantified with simple statistical measures like the coefficient of variation and standard deviation, which assess variability across multiple trials after generating an average (Davids et al., 2006; James, 2004). However, these measures only quantify the magnitude of variability, and assume a "typical" variability exists, without reference to how movement patterns exhibit variability over time (Caballero et al., 2014; James, 2004). Additionally, they assume variability is a deviation from an average, representing error (Caballero et al., 2014). Furthermore, by taking only a single measure from a continuous variable, such as kinematics from a walking gait, a large amount of information is discarded, resulting in the loss of potentially useful information (Preatoni et al., 2013). As such, linear measures of variability do not evaluate the structure of variability. Another limitation of linear measures is that they can only measure one of the temporal or spatial aspects of movement, whilst neglecting the other component (Longo et al., 2018).

Consequently, DST has led to a rise in the use of nonlinear analysis methods, which can characterise the structure of variability because they acknowledge the deterministic origin (i.e., different constraints) and the influence of constraint alteration on movement patterns (Hamill et al., 1999; Stergiou et al., 2004; Van Emmerik et al., 2004). As such, nonlinear analysis tools recognise that variability is inherent and important to functional human movement (Estep et al., 2017). Broadly, nonlinear tools analyse the repeated cycles of movement over time and attempt to evaluate the dynamics causing the changes that occur between cycles (Preatoni et al., 2013).

Various non-linear analysis techniques exist (and debate exists amongst researchers about what constitutes a nonlinear tool), each examining a unique aspect of data and thus comparisons should only be made between the same analysis techniques. As such, the tool being used is dictated by the question being answered (Benguigui et al., 2015). Defining the specific type of variability measure being applied is critical and the technique applied should be dictated by the question as different techniques analyse different aspects of movement, whether that be stability or variability (Cowin et al., 2022), which despite being related, represent different concepts (Longo et al., 2018). The specific relationship between variability (linear measure) and stability (non-linear measure) is context dependent, as typically an increase in the magnitude of variability represents decreased stability, but instances exist where movements are stable but exhibit variability (Smith et al., 2010).

One technique that analyses stability is the LyE, which is derived from chaos theory, a theory examining dynamic systems, which states that a system is influenced by its initial conditions (Straussfogel & von Schilling, 2009). Specifically, the LyE analyses the local dynamic stability of a system – the degree of sensitivity to small perturbations that exists in a system – by examining how neighbouring trajectories diverge from one another amongst data points at multiple time instances (Buzzi et al., 2003; Chang et al., 2010; Mehdizadeh, 2019; Toebes et al., 2012). The rate of convergence and divergence of trajectories indicate the dynamic stability of a system (Reynard & Terrier, 2015). A positive LyE value indicates greater variance/divergence in trajectories, a more unstable system and an inability to diminish local perturbations, whereas a negative LyE signifies trajectories converging more over time and a locally stable system (Mehdizadeh, 2018; Stenum et al., 2014; Stergiou et al., 2004). In order to calculate LyE, the state space of the dynamical system must be reconstructed, which requires determining an appropriate embedding dimension, the number of successive points in the dynamical system and time delay, an integer determining how many data points are included for analysis (Matilla-García et al., 2021) Two methods exist to analyse the LyE, the Rosenstein and Wolf methods, each examining movement trajectories but possess differences in their calculation (Wurdeman, 2018a).

Like many non-linear analysis techniques, the LyE has primarily been used to analyse walking gait and the factors that impact it, such as ageing (Terrier & Reynard, 2015), disease/injury (Beurskens et al., 2014; Reynard et al., 2014), and performing a secondary task (Sejdić et al., 2013). This has been prioritised due to the risk associated with falls and the impact a fall has on an individual's economic, physical and psychological health, of which instability during gait is a contributor to this risk (Mehdizadeh, 2018). The prominence of LyE walking gait literature resulted in Mehdizadeh (2018) conducting a systematic review of its application to walking gait. In this review, it was concluded that the different methodology researchers employ result in different LyE exponents being calculated. These methodological differences included experimentation methods like the method of capture (kinematic modelling or accelerometry), body segments/joints assessed, and data analysis methods such as different state space reconstructions (embedding dimension and time delay) or the LyE algorithm applied. Despite the LyE being suited to analyse perturbations during cyclic movements, the application of the LyE to other cyclic movements like cycling and running appears to be much scarcer in comparison to walking gait. However, to properly determine the application of LyE to other forms of movement, a systematic review is required, which to the author's knowledge had previously not been conducted.

As such, this review aims to address the following questions: What cyclic movements, excluding walking, have LyE been applied to? How has LyE been applied to analyse cyclic movement other than walking? Are there differences in the methodologies used?

Summarising the current literature using LyE to analyse human movement (excluding walking gait) will inform researchers of the prevalence of LyE application to other cyclic movements and potentially help guide the future use of LyE.

Methods

The structure of the review follows the PRISMA guidelines (Page et al., 2021). The protocol was developed using the Joanna Briggs Institute (JBI) Manual for Evidence Synthesis systematic review development recommendations (Aromataris & Munn, 2020; Peters et al., 2020) and was registered on Open Science Framework on 20 January 2022 to ensure methodology transparency (0.17605/OSF.IO/7BKND). All alterations from the protocol are documented in the relevant sections.

Eligibility criteria

Studies were selected if they adhered to the following criteria.

Inclusion criteria: Full-text peer-reviewed literature/journal articles that are primary original research studies; English-language papers or papers available in English; sporting movements assessed at the individual level; LyE applied.

Exclusion criteria: Secondary analysis of an intervention study, systematic reviews and meta-analyses; no full-text or English text available; literature that is not peer reviewed including but not limited to grey literature, websites, blogs, conference papers/abstracts; walking gait research studies; modelling and simulation studies; individual movement not assessed; LyE has not been applied to analyse biomechanical data.

Search strategy

A literature search of titles, abstracts and key-words was performed using Medline, EmCare, Embase Scopus and SPORTDiscus, as well as Web of Science databases on 20 February 2022 initially and updated on 1 June 2023 (Figure 1) using the search terms in Table 1.

Data collation/management

References from each database were exported to Endnote (Endnote 20.1, Clarivate analytics, London, United Kingdom) in separate folders to maintain records of each database. The Endnote library was exported in its entirety to Covidence (Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia) for title and abstract screening. Following database searching (both initial and the re-run), 1672 studies were identified (218 on the re-run). A total of 608 duplicates were removed in Covidence prior to tile and abstract screening, leaving 1213 articles to screen (1096 originally, 117 after the re-run).

Screening in covidence

Title and abstract screening was performed by the primary investigator (L.W.), were articles that were clearly not eligible were removed; any that were unclear were included. Following title and abstract screening, as well as reference list searching, 159 articles were eligible for full-text screening. Full-text screening was performed independently by the primary investigator and

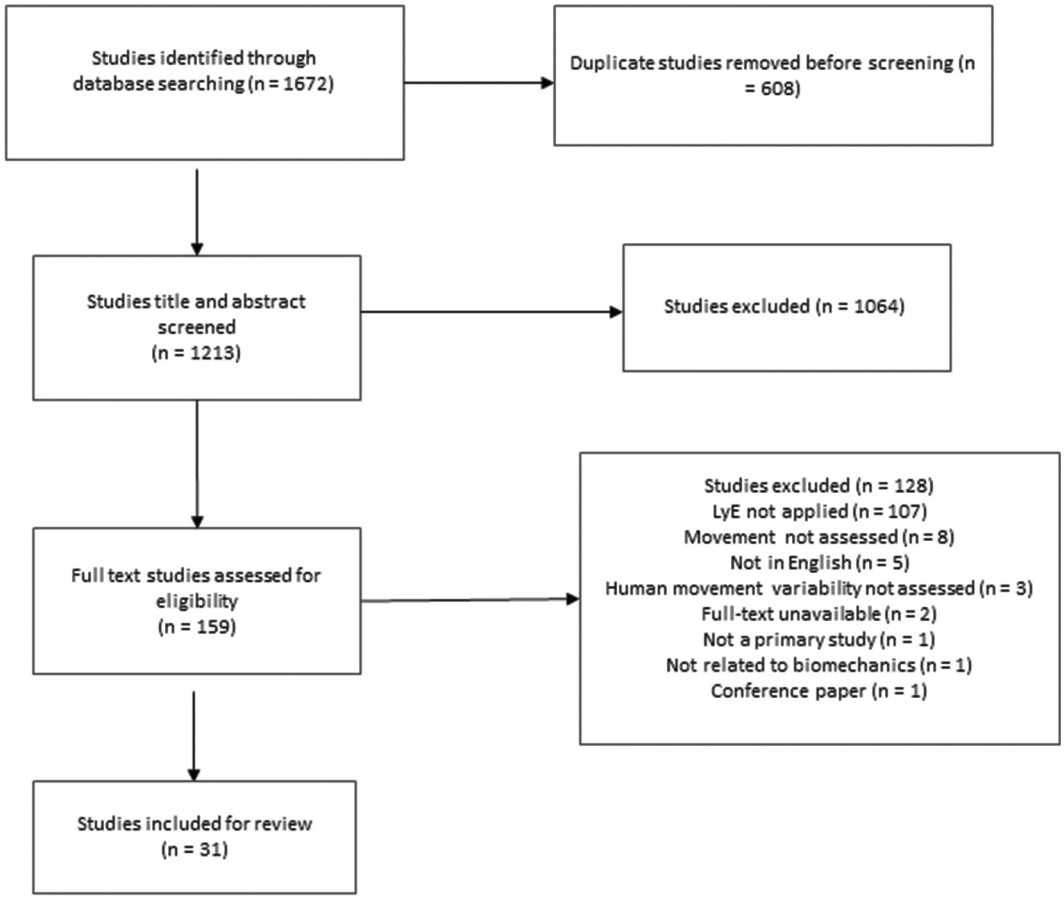

Figure 1. Flow chart of the database searching and screening process.

Table 1. Database search terms.

Line	Search terms combined with AND
1	(lyapunov exponent* OR divergence exponent OR dynamic stability OR movement variability).tw,kf.
2	Sports/
3	(sport* OR bicycl* OR swim* OR run* OR row* OR jump* OR basketball* OR throw* OR handball* OR cycling OR danc* OR athlet*).tw,kf.
4	Bicycling/
5	Swimming/
6	Dancing/
7	running/
8	athletic performance/
9	2 OR 3 OR 4 OR 5 OR 6 OR 7 OR 8
10	1 and 9

*=truncation, /= subject.

Table 2. Quality analysis form used in the systematic review.

Q1 – Are there clearly defined research questions?
Q2 – Was a power analysis conducted to determine the sample size required? - Optional
Q3 – Are the participant/athlete demographics defined?
Q4 – Is the inclusion/exclusion criteria of the study clearly defined?
Q5 – Were the participants exposed to a familiarisation protocol before data collection? - Optional
Q6 – From the information provided on the experimental protocol used, could the research be replicated?
Q7 – Were the methods used for Lyapunov Exponent clearly explained?
Q8 – Was the data used for the Lyapunov Exponent clearly defined?
Q9 – Was test-retest reliability performed or referenced?

Questions were scored as follows: 0 = no description; 1 = limited description; 2 = good description.

a second reviewer (P.T.). Disagreements on the relevance of an article were settled by a third reviewer (R.G.C.). The level of agreement between the researchers was reported using the Kappa statistic to determine inter-rater reliability where 0 is no agreement, 0.01–0.20 is none to slight, 0.21–0.40 is fair agreement, 0.41–0.60 is moderate, 0.6 1–0.80 is substantial and 0.81–0.99 is almost perfect agreement and 1 is perfect agreement. Figure 1 details the combined screening process (both initial and re-run) in flow chart form, utilising the PRISMA guidelines (Page et al., 2021).

Data extraction

Data was extracted by the primary investigator (LW) Table 3. Similar to Mehdizadeh (2018), the data extracted included the author, study aim/objective, participant number and characteristics (age, height and mass), data capture method, movement, apparatus, sampling rate, segment/joint assessed, data type, surrogation, filtering, embedding dimension (values, calculation and individualisation), time delay (values, calculation and individualisation), number of strides, time-series length, time normalisation, the algorithm applied and LyE values.

Quality assessment

Critical appraisal was performed to determine the quality of literature that exists in applying the LyE to other forms of movement. This was conducted by both reviewers (L.W. and P.T). The methodological quality assessment tool used was based off a tool implemented by Brown et al. (2014) and tailored to meet the requirements of this review. The quality assessment criteria were 0, 1 or 2, representing clearly did not answer question, maybe answered the question or inadequate information provided and clearly answered the question, respectively. Table 2 lists the questions that were used to analyse the quality of each article.

As such, the highest possible score is either 14, 16 or 18, depending on whether question 2 and/or question 5 is relevant to the study being critically appraised. Quality assessment was expressed as a percentage of the maximum score. A third reviewer (R.G.C.) resolved data extraction disputes if consensus was not reached.

Results

Overall, 159 studies were identified and 31 satisfied the inclusion/exclusion criteria and were retained for analysis (Figure 1). The inter-rater reliability of the full test screening process was $\kappa = 0.59$. Inter-rater reliability was low because initially there was a mis-communication between the reviewers, whereby one reviewer was excluding all gait studies including running.

Study characteristics

The included studies contained between 1 and 41 participants with a mean sample size of 18.1 ± 8.7. The mean participant age was 25.3 ± 5.0 yrs and ranged from 14.0 to 37.1 yrs. The mean participant height was 1.75 ± 0.04 m, while the mean participant body mass was 69.4 ± 4.9 kg. Age, height and mass were not reported in 2 [15, 24], 5 [11, 15, 24, 27–28] and 6 [10–11, 15, 24, 27–28] studies, respectively. Table 3 reports the study characteristics of studies employing the LyE to analyse movement variability. Studies utilising the LyE have analysed paddling/kayaking twice[10, 20], jumping once[14], basketball dribbling once[28], weighted raise once[27], skiing once[4], cycling twice[1, 24] and

Table 3. Characteristics of studies investigating the LyE.

Ref. No.	Study	DCM	Movement	Apparatus	Hz	Segment/ Joint	Data Type	Surrogation (Y/N)	Filtering (Y/N)	ED calc.	ED Ind. (Y/N)	ED	TD calc	TD ind. (Y/N)	TD	No. of strides	TN	ALG
1	Abbasi, Zamanian and Svoboda (2019)	MoCap/ EMG	Cycling	Ergometer	100 (MoCap)/ 1000 EMG	Hip, Knee, Ankle	Ang. Velo/ Disp + MA	NS	Y – 4 BW 10Hz	FNN	N	4 MoCap 5 EMG	AC	N	10 MoCap 4 EMG	30	Y	NS
2	Arshi, Mehdizadeh and Davids (2015)	MoCap	Running	Treadmill	100	Trunk	Marker Motion	NS	N	FNN	N	5	AMI	N	10	100	Y	ROS
3	Ataabadi et al. (2021)	MoCap	Running	Treadmill	100	Hip, Knee, Ankle	JA	NS	Y – 4 BW 8Hz	FNN	Y	5–6	AMI	Y	20	50	Y	NS
4	Cignetti, Schena and Rouard (2009)	MoCap	Skiing	Treadmill	100	Leg/Arm	Ang. Disp.	Y	N	FNN	NS	5	AMI	NS	26	30	Y	ROS
5	Ekizos, Santuz and Arampatzis (2017)	MoCap.	Running	Treadmill	190	Trunk	Vert. Disp.	NS	Y 4 BW 20 Hz	FNN	Y	3	AMI	Y	22–26	278	Y	ROS
6	Ekizos, Santuz and Arampatzis (2018)	MoCap	Running	Treadmill	170	Trunk	Vert. Disp.	NS	Y – 4 BW 20Hz	FNN	Y	3	AMI	Y	19–24	120 s	Y	ROS
7	Ekizos et al. (2018)	MoCap	Running	Treadmill	190	Trunk	Vert. Disp	NS	Y – 4 BW – 20Hz	FNN	NS	3	AMI	Y	21–27	279	Y	ROS
8	Fohrmann et al. (2022)	IS	Running	Treadmill/ Overground	128	Sternum/ Sacrum/ Tibia/Foot	Ang. Velo.	NS	N	FNN	N	9 sternum/ sacrum 6 Tibia	AMI	N	11 Sternum/ Sacrum 8 Tibia 10 Foot	100	Y	ROS
9	Frank, Prentice and Callaghan (2019)	MoCap	Running	Treadmill	100	Ankle/Knee/ Hip	JA	NS	Y – 2 BW 15 Hz	FNN	N	7 Ankle 6 Hip and Knee	AMI	Y	Reported in supp.	216	NS	W
10	Hamacher et al. (2018)	IS	Kayaking	Ergometer	100	Trunk/ Hands/ Upper arm	Ang. Velo.	NS	NS	FNN	N	12 hands 9 upper arms and trunk	AMI	N	13 arms 16 hands 22 trunk	70	Y	ROS
11	Hoenig et al. (20192019)	IMU	Running	Overground	100	Thorax/ Pelvis/ Foot	Ang. Velo.	NS	NS	FNN	Y	6 Foot + Pelvis 6–9 Thorax	AMI	Y	Foot 5–6; Pelvis 8–11 Thorax 10–12	150	Y	ROS
12	Hollander, Hamacher and Zech (2021)	IMU	Running	Treadmill	256	Shank	Ang. Velo	NS	NS	FNN	N	9	AMI	N	X = 7.6 Y = 12.2 Z = 11.8	3 int. of 100	Y	ROS

(*Continued*)

Table 3. (Continued).

Ref. No.	Study	DCM	Movement	Apparatus	Hz	Segment/ Joint	Data Type	Surrogation (Y/N)	Filtering (Y/N)	ED calc.	ED Ind. (Y/N)	ED	TD calc	TD ind. (Y/N)	TD	No. of strides	TN	ALG
13	Jordan et al. (2009)	MoCap	Running	Treadmill	125	Head, Ankle	Vert. Disp.	NS	Y – 2 BW 6Hz	FNN	NS	5	AMI	NS	0.192 s	5 min	NS	NS
14	Larson et al. (2021)	MoCap	Jumping	Overground	240	Ankle, Knee, Hip	JA	NS	Y – BW 6 Hz	FNN	Y	5.12	AC	Y	12.7	30	Y	ROS
15	Look et al. (2013)	MoCap	Running	Treadmill	300	Hip, Knee, Sacrum	JA/COM pos.	NS	NS	FNN	NS	3	AMI	NS	52–56	8–10	N	K
16	Mahaki et al. (2020)	IMU	Running	Treadmill	100	Trunk	Ang. Velo.	NS	N	FNN	N	8 sagittal 7 frontal + horizontal	AMI	Y	9–18 sagittal 13–25 frontal 13–24 horizontal	150	Y	ROS
17	Mehdizadeh, Arshi and Davids (2014)	MoCap	Running	Treadmill	200	ankle, knee, hip, sacrum	Marker Motion	NS	N	FNN	N	4	AMI	N	10	100	Y	ROS
18	Mehdizadeh, Arshi and Davids (2014)	MoCap	Running	Treadmill	100	Trunk	Marker Motion	NS	N	FNN	N	5	AMI	N	10	100	Y	ROS
19	Mehdizadeh, Arshi and Davids (2016)	MoCap	Running	Treadmill	100	Ankle	X, Y, Marker Velocity	NS	N	FNN	N	5	AMI	N	10	100	Y	ROS
20	Nessler et al. (2015)	MoCap	Paddling	Ergometer	120	Wrist	Vertical trajectory	NS	NS	FNN	NS	4	AMI	N	20	50 (approx.)	Y	ROS
21	Ogaya et al. (2021)	MoCap	Running	Treadmill	100	Ankle, Knee, Hip, Trunk	JA	NS	Y – BW 10 Hz	FNN	N	4	AMI	Y	18–24	30	NS	ROS
22	Padulo et al. (2023)	MoCap	Running	Treadmill	1000	N/A	Stride frequency	NS	NS	Delay embedding vectors	NS	NS	AC	NS	NS	100	NS	NS
23	Promsri (2022)	MoCap	Running	Treadmill	250	Whole Body	Posture Vector	NS	NS	FNN	NS	4	AMI	NS	10	NS	NS	W
24	Quintana-Duque and Saupe (2013)	MoCap	Cycling	Ergometer	100	Knee	JA	Y	NS	FNN	N/A	4	AC	N/A	21–33	NS	NS	W
25	Raffalt et al., (2019)	MoCap	Running	Treadmill	120	Sacrum	Marker pos.	NS	NS	FNN	Y	5	AMI	Y	22 A-P 15 Vert 29 M-L	80	Y	ROS + W
26	Raffalt et al., (2020)	MoCap	Running	Treadmill	120	Hip, Knee, Pelvis	JA/Sacrum Pos.	Ns	N	FNN	Y	NS	AMI	Y	NS	3 min	Y	W
27	Rahatabad et al. (2021)	EEG	Weighted Raise	Dumbbell	1000	Brain	EEG	NS	NS	NS	N	NS	NS	NS	NS	10	NS	NS
28	Robalo et al. (2021)	MoCap	Dribbling	N/A	120	Wrist, Elbow, Shoulder	Marker Coordinates	NS	NS	NS	NS	NS	NS	NS	NS	42	NS	NS
29	Santuz et al. (2018)	MoCap	Running	Treadmill	100	Trunk	Vertical Coordinates	NS	Y – 4 BW 50Hz	FNN	NS	NS	AMI	Y	36–40	287 (max)	Y	ROS

(*Continued*)

Table 3. (Continued).

Ref. No.	Study	DCM	Movement	Apparatus	Hz	Segment/ Joint	Data Type	Surrogation (Y/N)	Filtering (Y/N)	ED calc.	ED Ind. (Y/N)	ED	TD calc	TD ind. (Y/N)	TD	No. of strides	TN	ALG
30	Strongman and Morrison (2021)	MoCap	Running	Treadmill	250	Hip, Knee	JA	NS	N	FNN	N	5	AMI	N	18	2 min	NS	W
31	Walsh (2021)*	IMU	Running	Treadmill	100	Trunk/LB muscles	ACC/EMG	NS	Y 2 BW 20/2 Hz (IMU), 15Hz (EMG)	FNN	N	6	AMI	N	7 A-P 10 M-L 9 Vert	120	Y	ROS

REF = reference; DCM = data capture method; Hz = Hertz (sampling rate); Y = yes; *N* = no, NS = not stated; ED = embedding dimension, TD = time delay; calc. = calculation; TN = time normalization, ALG = algorithm; Ang. Velo = angular velocity; Ang. Disp = angular displacement; MA = muscle activity; BW = Butterworth filter; FNN = global false nearest neighbours method; AC = auto-correlation function; EMG = electromyography; AMI = average mutual information function; ROS = Rosenstein algorithm; Vert. disp. = vertical displacement; s = seconds; IS = inertial sensors; JA = joint angle; W = Wolf; IMU = inertial measurement unit; COM = Centre of mass; pos. = position; K = Kantz; min = minutes; ACC = acceleration; A-P = anterior-posterior, M-L = medio-lateral, vert = vertical; Int. = Interval; LB = lower body.

*no information presented on LyE calculation for muscle synergies.

predominately running, which occurred applied 23 times[2–3,5–9,11–13, 14–19, 21–23, 25–26, 29–31].

Methodological quality assessment

The methodological quality assessment is reported in Appendix 1. The mean quality of the 31 studies was 67.6%. The mean rating for sample size power analysis was 0.21 as it was conducted in three studies [3,23, 28] (10%) to justify their sample size. The mean rating for the description of participant demographics and explanation of the inclusion/exclusion criteria was 1.65 and 1.73, respectively. Whether participants were exposed to a familiarisation protocol had a mean rating of 0.73. Test replicability had a mean rating of 1.81. Whether the methods used to calculate the LyE were clearly explained and if the data used to calculate the LyE were clearly defined had a mean rating of 1.81 and 1.87, respectively. Test–retest reliability was performed or referenced in 10[3,4,6,8,12,16,21,22,24,29] studies (32%), possessing a mean rating of 0.48.

LyE protocol

Table 3 also reports the LyE methodologies that each study employed. LyE has been applied to inertial measurement units/sensors (IMUs) six times,[8,10–12,16,31], electroencephalography (EEG) once[27] and electromyography (EMG), twice[1,31]. Predominately, data was captured via motion capture (segment and joint angular kinematics) and was done so 24 times [1–7, 9, 13–15, 17–26, 28–30].

Sampling rate ranged in studies using motion capture from 100 to 1000 Hz, with 100 Hz being the most commonly used sampling rate, used 10 times[1–4, 9, 18–20, 21, 24, 29]. Similarly, the IMU sampling rate ranged between 100 and 256 Hz, whereby 100 Hz was the most commonly used sampling rate, used four times[10–11,16,31]. The sampling rate in the EEG[27] and EMG[1,31] (in both instances) studies was 1000 Hz.

Surrogation was only performed in two studies[4, 24]. Filtering occurred in 11[1,3,5–7,9,13,14,21,29,31] studies where a Butterworth filter was applied in all instances. Cut-off-frequencies ranged between 2.5 and 50 Hz, with 20 Hz being the most common (4 times). A 2nd and 4th order filter was applied 3[9, 13,31] and 6[1,3,5–7,29] times, respectively, and two studies did not report this information[14,21].

A range of segments/joints were analysed. In paddling, the upper extremity was analysed in both studies[10,20] and one also analysed the upper body (trunk)[10]. The repeated jumping study[14] assessed the lower body (ankle, knee and hip). In the two cycling studies[1, 24], the lower body was assessed. The upper extremity was analysed in the basketball dribbling study[28]. The upper extremity and lower body were assessed in the skiing study[4]. In running, the lower body was assessed in 12[3, 8,9,11–14,17,19,21,26,30] instances, the upper body in 11[2, 5–8, 11, 16,18,21,29,31], the pelvis in 6[8, 11,14,17,25–26], and the head[13] and whole body[23] in one instance each. Stride frequency (which is not associated with a joint) was assessed in one case[22]. The brain was assessed in the weighted raise (EEG) study[27].

The embedding dimension must be defined before the LyE is calculated. The global false nearest neighbours were the most commonly applied algorithm, applied in 28 cases[1–21,23–26,29–31]. Delay embedding vectors were implemented once[22] and how the embedding dimension was constructed was not reported in two cases[27, 28]. The embedding dimension was individualised in 7 instances[3,5–6,11,14,25–26], fixed (i.e., constant between participants) in 14[1–2,8–1012,16–19,21,27,30–31] cases and whether individualisation occurred was not stated in 9 instances[4,7,13,15,20,22–23,28–29]. In the case study, whether individualisation between participants was not applicable[27]. Embedding dimension values ranged between 3 and 12, with five being the most common value, similar to walking gait (Mehdizadeh, 2018) used in eight instances[2–4,13,18–19,25,30]. Embedding dimension values were not reported in five studies[22, 26–29].

Time delay like the embedding dimension must be defined before the LyE is calculated (Matilla-García et al., 2021). Within the non-walking gait movement literature, the average mutual information function is the most commonly applied algorithm to calculate it, used in 25 instances[2–13,15–21,23,25–26,29–31]. The autocorrelation function was applied in four instances[1,14,22,24], and how the time delay was calculated was not reported in two instances[27–28]. Time delay was individualised in 12 instances,[3,5–7,9,11,14,16,21,25–26,29] but it was either not reported whether it was individualised or not individualised in 7[4,13,15,22–23,27–28] and 11[1–2,8,10,12,17–20,30–31] studies, respectively. Time delay individualisation was not relevant in the case study[27]. Time delay was reported in two ways, as either a fixed number (26 instances[1–12,14–21,23–25,29–31]) or in seconds (2 instances)[4,13]. One study reported both seconds and a fixed number[4]. Time delays ranged between 5 and 56, with the most common occurrence being 10 (7 instances)[1–2,8,17–19,23,31,], similar to the walking gait as reported in (Mehdizadeh, 2018). Time delay values were not reported in four studies[22, 26–28].

The number of strides/cycles used varied, ranging between 8[15] and 287[29] steps in running, 50[20] and 70[10] in kayaking, 42 in basketball dribbling[28] and 30 cycles in cycling[1] and skiing[4] and 10 in the weighted raise[27]. The number of cycles/strides was not reported in two studies[23–24] or written as an interval of time in four studies[6,13,26,30]. Time-series length was reported in 16 studies[1–8,10–12,16,18–19,29,31] and not reported in 15 instances[9, 13–15,17,20–28,30,] Data was time normalised in 21 instances[1–8,10–12,1416–19,25–26,29,31], was not time normalised in one instance[15], and it was not stated whether time normalisation occurred in 9 instances[9,13,21–24,27–28,30].

The Rosenstein algorithm was the most widely adopted algorithm, applied in 19 studies[2,4–8,10–12,14,16–21,25,29,31,] Wolf's and Kantz algorithm was applied in 6[9,23–26.30] and 1[15] study, respectively. However, three papers did not specifically mention what algorithm they applied but referenced Rosenstein and Kantz in 2[3, 13] and 1[22] study, respectively. The algorithm used was not specified in three studies[1,27–28].

Due to the large range of LyE values that have been produced in the studies included in this review, even when analysing the same task, LyE values were not reported in text, and are instead reported in Appendix 2. This was particularly evident in the 23 studies that analysed running. As no study replication has occurred, it renders comparison of LyE values implausible.

Discussion

The aim of this review was to determine the breadth of current research applying the LyE to movements other than walking gait and determine if methodological differences exist between studies. Within the 31 studies that were included for the analysis, it was confirmed that methodological differences do exist within the literature applying the LyE culminating in a range of LyE values being produced. Additionally, running is the most commonly assessed non-walking gait movement when applying the LyE, utilised in 23 of the 31 included studies. Furthermore, research has commonly taken place using motion capture systems.

LyE protocol

Environment

Due to the large number of data points required when calculating the LyE, research analysing other activities has predominately been conducted on treadmills and/or ergometers. Similar to walking gait, it has been found that treadmill running produces a more stable running pattern than overground running (Fohrmann et al., 2022), which is likely due to the constraints of the environment. It has been demonstrated in various activities that removing a task from its original domain can alter movement expression (Pinder et al., 2011). For example, in cycling (Wilkinson & Lichtwark, 2021), concluded that ergometer alter the lateral dynamics of a bicycle, as they do not permit side-to-side movement. As such, future research should be conducted in ecologically valid domains to best capture the movement pattern that occurs during performance in realistic situations (Cowin et al., 2022). To do this, data must be captured with measurement tools that allow for greater ecological validity. One such tool is IMUs, portable devices that consist of a triaxial accelerometer, gyroscope and magnetometer (Schall et al., 2016). Despite their improved ecological validity and reduced cost, making them a more plausible and practical option, research has predominantly been done via motion capture. Twenty-four studies collected data via motion capture compared to six that captured data via IMUs in this review. Therefore, further research analysing the LyE should be applied using IMUs to improve the ecological validity of research applying the LyE to human movement.

Filtering

The purpose of filtering data is to remove unwanted noise and leave the relevant information (de Cheveigné & Nelken, 2019). However, within LyE research, it is recommended that filtering does not occur (or occurs with a high cut-off frequency) as it can affect the LyE calculation by potentially removing "true" fluctuations that occur, thus changing the dynamics of the system (Raffalt et al., 2020). Despite this, filtering occurred in 11 of the studies analysed, with varying cut-off frequencies, which is not best practice. Future LyE studies should avoid filtering data prior to calculating the LyE due to its potential effect on the results.

Sampling rate

An appropriate sampling rate is important as too small a sampling rate will result in information not being captured and too high a sampling rate will result in too much information being captured (Fallahtafti et al., 2021). Whilst studies have analysed the effect of data length (Hussain et al., 2020) and time normalisation (Raffalt et al., 2019) on the calculation of the LyE, to the author's knowledge, no study has analysed the effect of sampling rate on LyE calculation on kinematic data. This could be done in future investigations to ensure more similar methodologies occur between research applying the LyE.

Surrogation

Surrogation is a technique applied in non-linear analysis to determine if "true" non-linearity exists within a dynamic system (Faes et al., 2009). Specifically, it involves generating a null hypothesis, which assumes the system is linear, after which, the original data is transformed and a random data set is generated that retains some of the properties of the original time series (Lancaster et al., 2018). Within the LyE analysis, if the LyE of the original data differs significantly from the surrogate data, then it can be inferred that the original data is chaotic/deterministic (Stergiou et al., 2004). However, only two studies had performed a surrogate analysis to determine the non-linearity of the system; most researchers have assumed that non-linearity exists within their data set, without first establishing it. As such, future research applying the LyE to movement data (or any data assessing a dynamical system) should first run a surrogation analysis to determine if the data set has a chaotic origin. This is important because data that is completely random will produce a positive LyE just as chaotic data produce a positive LyE. Without a surrogate analysis, the difference between the two cannot be detected (Stergiou et al., 2004).

State space reconstruction

To calculate the LyE, the state space (the vector area where the dynamic system is defined) must be defined and involves determining the embedding dimension and time delay. There are several approaches to determine the embedding dimension and time delay, the most commonly used methods are the global false nearest neighbour and average mutual information function, respectively, consistent with walking gait literature (Mehdizadeh, 2018; Wurdeman, 2018b). However, different methods have also been reported to reconstruct the state space. Studies with different methodologies should not be compared as different state space reconstructions will affect the LyE calculation (Mehdizadeh, 2018; van Schooten et al., 2013). It is thought that each individual is a unique dynamic system due to possessing their own individual constraints (Davids et al., 2006). As such, it can be inferred that individual state space reconstruction should occur. Additionally, Raffalt et al. (2019) determined that the effectiveness of LyE calculation, regardless of which algorithm was applied, improved when individualising the time delay and embedding dimension. Individualisation of the time delay and

embedding dimension occurred in 12 and 7 occasions, respectively. Individualising the state space should occur in future research. More alarmingly, both how it was calculated, and values of the embedding dimension and time delay were not reported in three and four occasions for the embedding dimension and two and five occasions for the time delay, respectively. Failing to report this makes study replication difficult, particularly as these values will impact the LyE calculation because state space reconstruction is a precursor to determining the LyE (Amirpourabasi et al., 2020; Wurdeman, 2018b).

Time series length

The number of strides/cycles influences LyE calculation and as such should be reported (Bruijn et al. 2009). This did not occur in two studies, making repeatability of the study implausible. Furthermore, due to the impact of the number of cycles/strides on the calculation of the LyE, studies should implement a fixed number of strides/cycles to compare the LyE between different conditions (Mehdizadeh, 2018). The number of strides analysed will affect time-series length which impacts the calculation of the LyE (Mehdizadeh, 2018). Similarly, the LyE calculation is also affected by whether time normalisation occurs prior to it, hence it should be reported if it took place (Raffalt et al., 2019; Stenum et al., 2014). However, in 10 instances, studies either did not time normalise their data or state whether time normalisation occurred.

Algorithm

Consistent with the walking gait literature (Mehdizadeh, 2018), the most commonly applied algorithm is the Rosenstein algorithm. However, six studies either did not report or did not explicitly state the algorithm they used, which is problematic. Both the Wolf and Rosenstein algorithms calculate the LyE in different ways, which leads to different results (Raffalt et al., 2019). For example, when using the same lower limb data set, Cignetti et al. (2012)demonstrated that that different results were produced from the Rosenstein and Wolf algorithms, where the Rosenstein algorithm underestimated the LyE, and the Wolf algorithm overestimated it. As such, due to the different results they may produce, it is best practice to report the algorithm applied for transparency.

A broad range of LyE values exist, even for the same activity. Similar to Mehdizadeh (2018), the broad range of LyE reported is due to the broad range of methods being employed to calculate the LyE. However, another cause is the different research questions that have been answered. Because of this, it is difficult to generate normative values and determine what constitutes an acceptable LyE value for a given activity. As such, it is important that comparisons of the LyE only be made to other studies that are attempting to answer a similar question and employ the same or very similar methods (i.e., similar participant characteristics, state space reconstruction and capture method).

Quality assessment

The mean quality of the 31 studies was 67.6%. This quality score was generated through items 1 (clear research questions), and 6–8 (was the experimental protocol clearly detailed?, where the methods used for the LyE clearly detailed? and was the data used to calculate the LyE clearly defined?) which suggest that the majority of the studies are repeatable. However, a power analysis was performed in 3 of 28 eligible studies (11%) of studies. Within biomechanics, an insufficient sample size is an issue that continues to persist (Oliveira & Pirscoveanu, 2021), likely stemming through difficulties with recruitment. However, power analyses are required to determine the required sample size needed to see whether the results obtained are significant or not (Kemal, 2020). As such, this should be addressed in future research. Test–retest reliability determines the repeatability of a measurement and involves repeating the same measurement more than once (Hopkins, 2000). As such, it determines the consistency of the measurement. However, only 10 studies (32%) referenced reliability, resulting in a mean score of 0.48. However, only one study performed test re-test reliability which future studies should address this to better determine if the observed variability changes as calculated by the LyE are "real" or not.

Conclusion

Similar to walking gait (Mehdizadeh, 2018), discrepancy in calculating the LyE to analyse dynamic stability exists in experimental design (i.e., the question the researchers are trying to answer), data pre-processing (i.e., filtering and sampling rate) and the LyE calculation method (i.e., algorithm and state space reconstruction). This renders comparison of LyE values (even when comparing the same task) implausible. Additionally, there exist limitations in the current research applying LyE, namely the lack of research conducting a surrogation analysis prior to LyE calculation to determine whether the data does have a chaotic origin, and the lack of ecological validity in the current research (which could be addressed better through the use of devices like IMUs). Furthermore, there is a scarcity of test–retest reliability analysis that has been conducted which is necessary to determine if changes in the LyE are "real" or not. Addressing these limitations and others that have been presented will improve the application of the LyE.

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Appendix 1: Methodological quality assessment

Ref No.	Study	1.	2.	3.	4.	5.	6.	7.	8.	9.	Total score (18 points max)	Quality (%)
1	(Abbasi, Zamanian and Svoboda 2019)	2	0	2	2	2	2	1	2	0	13	72.2
2	(Arshi, Mehdizadeh and Davids 2015)	2	0	2	2	2	1	2	2	0	13	72.2
3	(Ataabadi et al. 2021)	2	2	2	2	1	2	2	2	1	16	88.9
4	(Cignetti, Schena and Rouard 2009)	2	0	1	2	0	2	2	2	1	12	66.7
5	(Ekizos, Santuz and Arampatzis 2018)	2	0	2	2	0	2	2	2	0	12	66.7
6	(Ekizos et al. 2018)	2	0	2	2	2	2	2	2	2	16	88.9
7	(Ekizos, Santuz and Arampatzis 2017)	2	0	2	2	2	2	2	2	0	14	77.8
8	(Fohrmann et al. 2022)	2	0	2	2	1	2	2	2	2	15	83.3
9	(Frank, Prentice and Callaghan 2019)	2	0	2	2	0	1	2	1	0	10	55.6
10	(Hamacher et al. 2018)	2	N/A	0	2	N/A	2	2	2	0	10	71.4
11	(Hoenig et al. 2019)	2	0	2	2	0	2	2	2	0	12	66.7
12	(Hollander, Hamacher and Zech 2021)	2	0	2	2	0	2	2	2	1	13	72.2
13	(Jordan et al. 2009)	2	0	1	0	2	2	2	2	0	11	61.1
14	(Larson et al. 2021)	2	0	2	1	0	1	2	2	0	10	55.6
15	(Look et al. 2013)	1	0	0	1	0	2	2	2	0	8	44.4
16	(Mahaki et al. 2020)	1	0	2	2	2	2	2	2	2	15	83.3
17	(Mehdizadeh, Arshi and Davids 2014a)	2	0	2	2	1	2	2	2	0	13	72.2
18	(Mehdizadeh, Arshi and Davids 2014b)	2	0	2	1	1	2	2	2	0	12	66.7
19	(Mehdizadeh, Arshi and Davids 2016)	2	0	2	2	1	2	2	2	0	13	72.2
20	(Nessler et al. 2015)	2	0	2	2	0	2	2	2	0	14	77.8
21	(Ogaya et al. 2021)	2	0	2	2	0	2	2	2	2	14	77.8
22	(Padulo et al. 2023)	2	0	2	2	0	2	2	2	2	14	77.8
23	(Promsri 2022)	2	2	2	1	0	2	2	1	0	12	66.7
24	(Quintana-Duque and Saupe 2014)	0	N/A	0	0	0	0	1	2	1	4	25
25	(Raffalt et al. 2020)	2	0	2	2	0	2	2	2	0	12	55.6
26	(Raffalt et al. 2019)	2	0	2	2	0	1	2	2	0	11	61.1
27	(Rahatabad et al. 2021)	1	N/A	0	N/A	0	2	0	0	0	3	21.4
28	(Robalo et al. 2021)	2	2	1	2	0	2	0	2	0	11	61.1
29	(Santuz et al. 2018)	2	0	2	2	2	2	2	2	1	15	83.3
30	(Strongman and Morrison 2021)	2	0	2	2	1	2	2	2	0	13	72.2
31	(Walsh 2021)	2	0	2	2	2	2	2	2	0	14	77.8
Mean		1.84	0.21	1.65	1.73	0.73	1.81	1.81	1.87	0.48	12.1	67.6

Ref = reference; no. = number; max = maximum; 0, clearly no; 1, maybe or inadequate information; 2, clearly yes.

Appendix 2: LyE Extraction Values

Ref No.	Study	Running	No. of Groups/Conditions	Segment/Joint	LyE Range
1	(Abbasi, Zamanian and Svoboda 2019)	Cycling	3 Without stretching (WS), Static stretching (SS), Dynamic stretching (DS)	Ankle, Knee, Hip (joint angles) Soleus (SL), Rectus Femoris (RF), Biceps Femoris (BF), Tiblias Anterior (TA), Gastrocnemius (G), Vastus Medialis (VM) (EMG)	Hip – 0.96 – 1.00 Knee – 0.53 – 0.86 Ankle – 0.97 – 1.25 SL – 0.68 – 0.89 RF – 0.73 – 1.09 BF – 0.62 – 1.10 TA – 0.54 – 0.99 G – 0.90 – 1.18 VM – 0.63 – 1.09
2	(Arshi, Mehdizadeh and Davids 2015)	Running	2 – Fw + La	Trunk	Fw- AP 1.57, ML 1.05 La AP 1.15, ML 2.01
3	(Ataabadi et al. 2021)	Running	3 conditions SSR, PSR, FSR	Ankle, Knee, Hip	Ankle – SSR 1.244 – 1.404, PSR 1.293 – 1.383, FSR 1.379 – 1.471 Knee – SSR 0.916 – 1.269, PSR 0.945 – 1.242, FSR 1.045 – 1.321 Hip – SSR 1.252 – 1.426, PSR 1.68 – 1.426, FSR 1.286 – 1.479
4	(Cignetti, Schena and Rouard 2009)	Skiing	surrogation vs. regular LyE's B + E	Leg, Arm	Arm Regular B – 0.18, E – 0.24 Surrogated B – 0.34, E 0.38 Leg Regular B – 0.22, E – 0.28 Surrogated B – 0.35, E 0.38
5	(Ekizos, Santuz and Arampatzis 2018)	Running	3 – LT, ST, CG Pre vs. Post	Trunk	ST – 1.81 – 1.86 LT – 1.78 – 1.79 CG – 1.80 – 1.75
6	(Ekizos et al. 2018)	Running	6 marker sets	Trunk	1.67 – 1.97
7	(Ekizos, Santuz and Arampatzis 2017)	Running	Shod vs. Barefoot	Trunk	Shod – 1.62 – 1.95 Barefoot – 1.68 – 2.08
8	(Fohrmann et al. 2022)	Running	3 conditions – T, OO, OI	Sternum, Sacrum, Tibia, Foot	Sternum – T 1.77 – 1.91, OO – 1.84 – 2.00, OI 1.85 – 2.00 Sacrum – T 4.28 – 4.39, OO 4.44 – 4.50, OI 4.45 – 4.53

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Ref No.	Study	Running	No. of Groups/Conditions	Segment/Joint	LyE Range
					Tibia – T 4.43 – 4.46, OO – 4.89 – 4.96, OI 4.90 – 4.92
					Foot – T 2.34 – 2.45, OO 2.56 – 2.67, OI 2.57 – 2.62
9	(Frank, Prentice and Callaghan 2019)	Running	4 shoe types – novice vs. trained	Ankle, Knee, Hip	Ankle Novice 1.41 – 1.49 Trained 1.19 – 1.23
					Knee Novice 1.21 – 1.25 Trained 0.72 – 0.76
					Hip Novice 1.13 – 1.21 Elite 0.61 – 0.64
10	(Hamacher et al. 2018)	Kayaking	1	Trunk, Left and Right UA, left and right hand (H)	Trunk – 0.001
					Left UA – 0.658
					Right UA – 0.634
					Left Hand – 0.254
					Right Hand – 0.165
11	(Hoenig et al. 2019)	Running	2 groups – C vs. R B, M, E	Thorax, Pelvis, Foot	Thorax C – 0.91 – 0.93 R – 0.90 – 1.01
					Pelvis C – 2.42 – 2.54 R – 2.64 – 2.84
					Foot C – 6.98 – 7.04 R – 7.23 – 7.33
12	(Hollander, Hamacher and Zech 2021)	Running	Shod vs. Barefoot – B, M, E	Shank	BShod 47.25 – 48.46Barefoot 49.03 – 50.74
					M Shod 47.71 – 48.14 Barefoot 48.99 – 50.12
					E Shod 48.14 – 48.71 Barefoot 49.55 – 51.04
13	(Jordan et al. 2009)	Running	5 speeds	Head, Ankle	Ankle – 0.080 - 0.092
					Head – 0.063 – 0.070
14	(Larson et al. 2021)	Jumping	2 groups PU vs. PI	Ankle, Knee, Hip	Ankle PU – 0.04 – 0.17 PI 0.07 – 0.17
					Knee PU - 0.04 – 0.16 PI 0.04 – 0.17
					Hip PU 0.04 – 0.17 PI 0.06 – 0.17
15	(Look et al. 2013)	Running	2 Groups – amputation (A) vs. no amputation (NA) Different speeds ranging from 3 – 9 m/s	Hip, Knee, Sacrum	NA – knee – 0.095 – 0.137 m/s A 0.090 – 0.138

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Ref No.	Study	Running	No. of Groups/Conditions	Segment/Joint	LyE Range
					Hip – 0.098 – 0.119 NA 0.075 – 0.131 A
					Sacrum ML A 0.006 – 0.16 Vertical (vert) A 0.09 – 0.20 NA ML 0.02 – 0.24 NA vert 0.19 – 0.25
16	(Mahaki et al. 2020)	Running	Pre – Post (recorded every min, 3 minutes after test completion)	Trunk	Sagittal (pre) 0.50 – 1.41; (post) 0.48 – 1.58
					Frontal (pre) 1.33 – 2.14; (post) 0.96 – 2.73
					Horizontal (pre) 0.37 – 3.02, (post) 0.33 – 2.75
17	(Mehdizadeh, Arshi and Davids 2014a)	Running	2 conditions – forward (Fw) and backward (B) running; 2 groups (skilled (S) vs. unskilled (US))	Ankle, Knee, Hip, Sacrum	Ankle Fw S 2.27 – 3.06, B S 2.20 – 3.28, Fw US 3.89 – 5.33, B US 3.62 – 4.83
					Knee Fw S 2.56 – 2.69, B S 2.35 – 2.65, Fw US 4.36 – 4.98, B US 3.89 – 4.71
					Hip Fw S 1.70 – 2.47, B S 1.93 – 2.64, Fw US 3.05 – 3.92, B US 3.10 – 3.98
					Sacrum Fw S 1.32 – 2.10, B S 1.69 – 2.25, Fw US 1.74 – 2.55, B US 1.45 – 2.19
18	(Mehdizadeh, Arshi and Davids 2014b)	Running	2 running speeds (80, 100, 120% preferred running speed) – long term (LT) vs. short term (ST) LyE B vs. Fw running	Trunk	Fw ST – 80% 1.15 – 1.45, 100% 1.14 – 1.55, 120% 1.25 – 1.53
					B ST – 80% 1.50 – 2.16, 100% 1.69 – 2.41, 120% 1.78 – 2.38
					Fw LT – 80% 0.01 – 0.08 100% 0.02 – 0.09, 120% 0.01 – 0.09
					B LT – 80% 0.03 – 0.08, 100% 0.03 – 0.11, 120% 0.03 – 0.10
19	(Mehdizadeh, Arshi and Davids 2016)	Running	3 running conditions – Fw, B, Lateral (La) 3 Speeds	Ankle	80% - Fw ML 1.03 AP 1.18; B ML 1.43, AP 1.76; La ML 1.55, AP 1.27
					100% - Fw ML 1.02, AP 1.18; B ML 1.41, AP 1.79; La ML 1.55, AP 1.32
					120% - Fw ML 1.02, AP 1.22; B ML 1.40, AP 1.74; La ML 1.55, AP 1.32
20	(Nessler et al. 2015)	Paddling	Wetsuit vs. Non-wetsuit	Wrist	Wetsuit – 1.49
					Non-Wetsuit – 1.38

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Ref No.	Study	Running	No. of Groups/Conditions	Segment/Joint	LyE Range
21	(Ogaya et al. 2021)	Running	Pre vs. Post	Ankle, Knee, Hip, Lumbar Spine	Ankle FL/Ex 0.85 vs. 0.90 Inv/Ev 0.65 vs. 0.71 Knee FL/Ex 1.04 vs. 1.04 Hip FL/Ex 1.00 vs.1.01 Abd/Add 0.74 vs. 0.78 INT/EXT 0.52 vs. 0.55 Lumbar Spine FL/EX 0.38 vs. 0.50 La bend 0.46 vs. 0.57 Rotation 1.19 vs. 1.19
22	(Padulo et al. 2023)	Running	3 conditions – 0% gradient (0CON), 2% gradient fixed speed (2CON), 2% gradient at isoefficiency speed (2IES)	N/A – Stride Frequency	0CON - 0.007 2CON 0.020 2IES 0.009
23	(Promsri 2022)	Running	5 principal movements in running – males (M) and females (F)	Whole Body	M 2.2 5.7 F 2.3 – 7.5
24	(Quintana-Duque and Saupe 2014)	Cycling	4	Knee	Knee Angle • 140 N 100 rpm 0.22 • 120 N 100 rpm 0.19 • 140N 80rpm 0.21 • 120N 80rpm 0.32 Knee x-coordinate • 140 N 100 rpm 0.18 • 120 N 100 rpm 0.24 • 140N 80rpm 0.20 • 120N 80rpm 0.26
25	(Raffalt et al. 2020)	Running	8 Speeds	Hip, Knee, Ankle, Pelvis	Hip 0.27 – 0.58 Knee 0.32 – 0.43 Ankle 0.60 – 0.82 COM displacement AP 1.79 - 0.48 - 0.70 ML 0.72 - 1.04 Vert 1.79 - 0.67 - 0.76

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Ref No.	Study	Running	No. of Groups/Conditions	Segment/Joint	LyE Range
26	(Raffalt et al. 2019)	Running	4 normalisation (N) procedures 2 algorithms at 2 speeds (1.79, 2.46)	Sacrum	Rosenstein N1 1.79 - 0.86 – 1.79 2.46 - 0.85 - 1.67 N2 1.79 - 0.83 - 1.64 2.46 - 0.82 - 1.64 N3 1.79 - 0.92 - 1.72 2.46 -, 0.94 - 1.72 N4 1.79 - 0.93 - 1.61 2.46 - 0.95 - 1.61 Wolf N1 1.79 – 1.75 - 2.28 2.46 - 1.62 – 2.46 N2 1.79 - 1.80 – 2.19 2.46 - 1.62 – 2.37 N3 1.79 - 1.36 - 1.67 2.46 - 1.27 – 1.88 N4 1.79 - 1.28 – 1.55 2.46 – 1.15 – 1.77
27	(Rahatabad et al. 2021)	Weighted Raise	5 Sensory Motor Areas	Brain	1.12 – 1.40
28	(Robalo et al. 2021)	Basketball Dribbling	Amateur vs. Professional 4 conditions NO – no occlusion VO – visual occlusion AO – auditory occlusion BO – both occlusion	Wrist, Elbow, Shoulder	Amateurs Wrist • NO 2.90 - 3.20 • VO 2.61 – 2.97 • AO 3.11 – 3.42 • BO 2.80 – 3.07 Elbow • NO 3.10 – 3.51 • VO 2.81 – 3.61 • AO 3.03 – 3.85 • BO 2.69 – 3.35 Shoulder • NO 1.75 – 3.39 • VO 1.36 – 2.12 • AO 2.34 – 3.81 • BO 1.37 – 2.19

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Ref No.	Study	Running	No. of Groups/Conditions	Segment/Joint	LyE Range
					Professionals Wrist • NO – 2.17 – 3.00 • VO 2.47 – 3.83 • AO 2.40 – 3.75 • BO 2.20 – 3.87 Elbow • NO – 2.87 – 3.92 • VO – 2.84 – 3.83 • AO – 2.58 – 3.75 • BO – 2.48 – 3.87 Shoulder • NO – 2.19 – 2.68 • VO – 2.52 – 2.77 • AO – 2.45 – 2.53 • BO 2.28 – 2.71
29	(Santuz et al. 2018)	Running	Unstable vs. Even	Trunk	Unstable - 2.031 Even - 1.936
30	(Strongman and Morrison 2021)	Running	3 Speeds Froude Fixed Self-selected	Hip, Knee	Hip Froude 0.84 – 2.16 Fixed 0.85 – 2.03 Self-selected – 0.58 – 2.37 Knee Froude 0.78 – 1.84 Fixed 0.95 – 2.18 Self-selected – 0.92 – 2.18
31	(Walsh 2021)	Running	Single Task vs. Dual Task	Trunk (JA); Muscle synergy	L5 ST PRS - 1.80 - 5.35 ST PRS 120 - 1.89 – 4.85 DT PRS – 2.19 – 5.31 DT PRS 120 – 1.94 – 5.31 Muscle Synergy ST PRS – 0.26 – 0.30 ST PRS 120 – 0.27 – 0.30 DT PRS – 0.26 – 0.29 DT PRS 120 – 0.26 – 0.29

Fw = forward, La = lateral, AP = anterior-posterior, La = lateral, SSR = Slow speed running, PSR = preferred-speed running, FSR = fast-speed running, B = beginning, E = end, LT = Long-term, ST = Short-term (ST), CG = Control. T = treadmill, OO = overground outdoor, OI = overground indoor, UA = upper arm, C = competitive, R = recreational, M = middle, PU = previously un-injured, PI = previously injured.