Title:

A scoping review of non-linear analysis approaches measuring variability in gait due to lower body injury or dysfunction

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Highlights

Chronic injury results in a more rigid gait, and also increased local dynamic stability.

Research is limited when considering injury and dysfunction, and future studies should consider other joints and movement planes.

Non-linear analysis is a useful tool to inform future clinical processes when dealing with rehabilitation of injury and movement variability.

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Abstract

Objectives

The aim of this review is to evaluate and summarize existing literature using non-linear analysis methodology to consider variability of human movement due to lower limb injury or dysfunction.

Design

Scoping review.

Methods

An electronic keyword search was performed on three databases to identify appropriate research. This research was then examined for details of measures and methodology, use of control groups and general study characteristics to identify related themes.

Results

Fifteen papers were reviewed and synthesized. A range of conditions were studied, mainly affecting knee and ankle joints, and each using different non-linear methods and different equipment (motion capture, accelerometry, and muscle activation) to evaluate the mathematically chaotic nature of the movement and assess the variability in gait. Sample sizes and effect sizes are commonly small in these studies.

Conclusions

Non-linear analysis is a potentially useful tool in both diagnosis and evaluation of injury, and this should inform future clinical processes when dealing with injury and movement variability. Despite numerous studies evaluating neurological conditions and ageing, focus on injury is limited, with notable gaps in terms of considering other joints and joint actions, so this should be a promising area of research to develop our understanding of injury and rehabilitation and how this affects gait variability.

Keywords

Non-linear analysis, injury, variability, gait, review.

1. Introduction

Gait variability is inherent in human movement as there are normal variations that occur each time a movement is repeated – each step is not identical to the one before. Injury and dysfunction can alter these movement patterns, leading to the gait patterns becoming “overly rigid and robotic or noisy and unstable” (Stergiou and Decker, 2011). An ideal level of gait variability lies somewhere between these two cases.

Rather than being random, these slight changes in gait pattern have a temporal structure, and mathematical tools relating to chaos theory can be applied to evaluate this (Stergiou and Decker, 2011). Linear measures such as coefficient of variation can only investigate the magnitude of variability, rather than evaluating any divergence from a stable and regular pattern. A non-linear analysis approach is required to investigate this temporal, dynamic aspect of variability (Harbourne and Stergiou, 2009)

Within gait analysis, various features could be analyzed to assess the level of movement variability, for example stride length or stance time (Heiderscheit, 2000), in addition to joint angle data (Stergiou and Decker, 2011). Stability of a dynamical system relates to how sensitive the system is to the initial conditions, and is commonly evaluated with Lyapunov exponents (Stergiou et al, 2004), whereas rigidity and predictability of a system can be evaluated by calculating the entropy of the time series (Yentes, 2017).

While there is a wide range of research considering neurological impairment (Moon et al, 2016) or falls risk (Hamacher et al, 2011) and how this relates to joint variability, research considering variability as a result of injury is more limited. This review aims to synthesize existing literature examining effects of lower body musculoskeletal injury or dysfunction on gait variability using a non-linear approach, in order to examine shared characteristics between previous studies both in terms of methodology and measure evaluated, and to identify any gaps that may exist. The way in which studies develop over time should give clear indications of areas of best practice, and possible exclusions, as well as providing justification for future work in this area.

2. Methods

An electronic search of three databases was performed (PubMed, SportDiscus and Web of Science) using keywords (variability OR *stability OR complexity) AND (nonlinear OR non-linear OR chaos OR chaotic OR perturbation* OR rigid* OR random* OR fluctuat* OR *regular* OR *control*) AND (gait OR walk* OR jog* OR run*) AND (injur* OR joint). In addition, Google Scholar was used to check for any grey literature. Publication time was not restricted to ensure all relevant literature was identified for screening. The literature search was performed on 20-23rd October 2019.

Studies met the inclusion criteria if they were human studies of lower body musculoskeletal injury or dysfunction with a non-linear analysis approach and dynamic movement/gait analysis. To ensure consistency of comparison, studies that only compared specific interventions (such as type of surgery) were excluded unless they also compared pre-operative patients with healthy control groups to consider the effect of the injury on movement variability. Studies considering amputees or prosthetics were excluded, as amputees have a specific, common gait pattern compared to non-amputees (Varrecchia et al, 2019).

Studies considering electromyography (EMG) to evaluate variability of muscle activation were only included if they also considered aspects of movement variability, such as joint angles.

No restrictions on gender or age were applied. Conference papers were excluded, as were reviews, but review papers were manually checked to ensure appropriate studies included in those reviews had been selected in the inclusion criteria here. Included papers were manually screened to ensure all appropriate citations were also considered for inclusion.

One author (CS) performed the initial search and applied the exclusion criteria, both authors screened the studies and evaluated the quality of the included papers.

Studies reported both significant and insignificant results, both accepting and rejecting their initial hypothesis, which suggests that publication bias is unlikely to be an issue in the studies found.

3. Results

3.1 Search results

The results retrieved in the search are presented in figure 1. Initially 1812 records were identified once duplicates were removed, and the abstracts were screened to exclude inappropriate studies. Papers were also full text screened to ensure that they evaluated an injury rather than an intervention, and three were excluded at this point as no pre-intervention data were available.

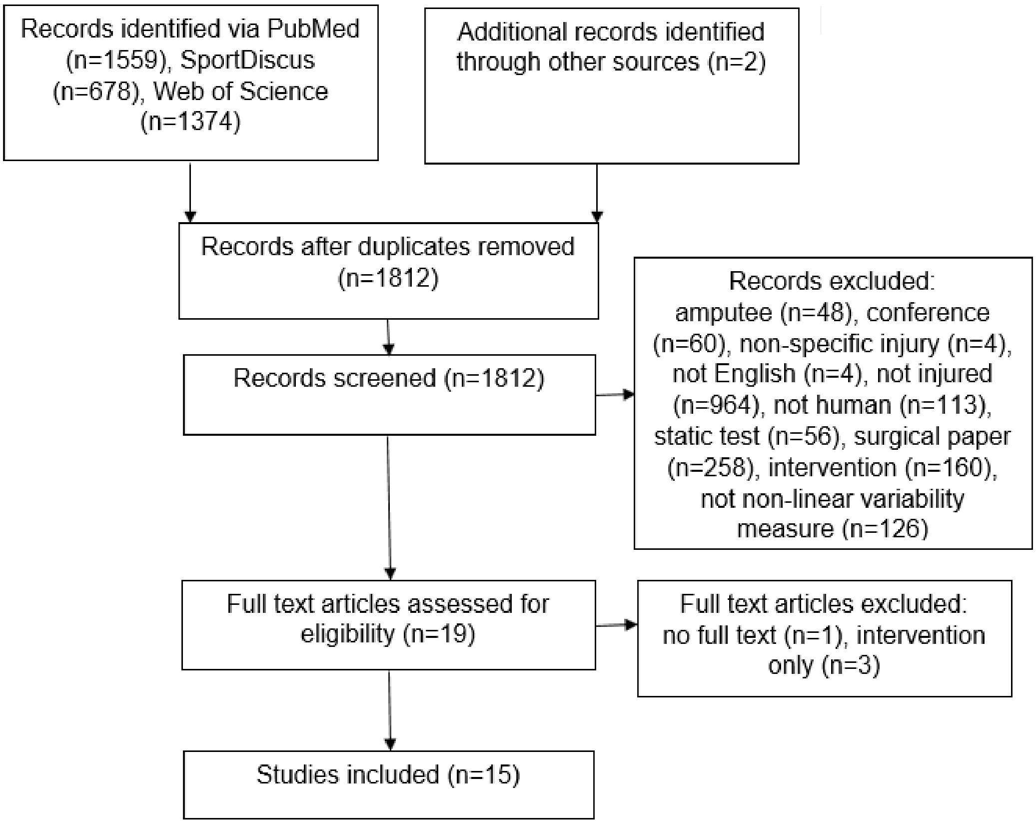

Figure 1:Search strategy using PRISMA guidelines (Moher et al, 2009)

3.2 Sample Characteristics

Of the fifteen studies shortlisted for review, six considered anterior cruciate ligament (ACL) deficiency (Stergiou et al, 2004a; Georgoulis et al, 2006; Moraiti et al 2007; Zampeli et al, 2010; Tzagarakis et al, 2010; Nazary-Moghdam et al, 2019), five studies considered knee osteoarthritis (OA) (Yakhdani et al, 2010; Tochigi et al, 2011; Alkjaer et al, 2015; Mahmoudian et al, 2016; Tanimoto et al, 2017), two on medial tibial stress syndrome (MTSS) (Rathleff et al, 2011; Schütte et al, 2018), with single studies on patellofemoral pain syndrome (PFPS) (Rathleff et al, 2013) and chronic ankle instability (Terada et al, 2015). Relevant characteristics of the participants in the studies are summarized in table 1, grouped by injury for comparison.

Table 1: Basic sample characteristics grouped by injury type.

	Location	Injury	Mean age	Gender	Mean height (cm)	Mean weight (kg)	Control
Stergiou et al, 2004a	USA	ACL	35.1	8F 2M	171	78.5	Contralateral leg
Georgoulis et al, 2006	Greece	ACL	34.7	8M 2F	173	77.3	Contralateral leg
Moraiti et al, 2007	Greece	ACL	34 9	5M 2F	170	75.0	Age and gender matched healthy.
Zampeli et al, 2010	Greece	ACL	27.1	15M	173	75.0	Age and gender matched healthy.
Tzagarakis et al, 2010	Greece	ACL	30.8	20M	177	78.6	Age and gender matched healthy.
Nazary-Moghadam et al, 2019	Iran	ACL	25.9	22M	179	83.0	Age and gender matched healthy.
Yakhdani et al, 2010	Netherlands	Knee OA	62.3	5M 11F	170	85.9	5M 7F age matched, healthy.
Tochigi et al, 2011	USA	Knee OA	No mean stated	35F 17M	Not recorded	Not recorded	30F, 27M, age matched control. Wide age range in asymptomatic group.
Alkjaer et al, 2015	Denmark	Knee OA	66.1	11F	Not recorded	Not recorded	Age and gender matched healthy.
Mahmoudian et al, 2016	Belgium	Knee OA	62.3	5M 11F	170	85.9	5M 7F age matched, healthy.
Tanimoto et al, 2017	Japan	Knee OA	73	10F 2M	152	54.3	Gender matched control, mean 66.
Rathleff et al, 2011	Denmark	MTSS	27.8	No gender reported.	173	77.8	11 age matched healthy.
Schutte et al, 2018	Belgium	MTSS	20.4	8M 6F	177	68.3	Age and gender matched healthy.
Rathleff et al, 2013	Denmark	PFPS	17.2	57F	166	58.7	29F age matched healthy.
Terada et al, 2015	USA	Chronic ankle instability	22.5	14M 11F	171	76.2	10M, 17F age matched controls.

As each condition commonly affects different population groups, ages used in the sample populations varied between conditions, but were broadly consistent, with arthritis typically affecting older people than PFPS.

With the exception of PFPS, both male and female participants were included for analysis, this is due to most conditions affecting both genders, but with PFPS predominantly affecting females (Rathleff et al, 2013). However, studies on ACL in particular have suggested that gender may affect injury and variability, so later studies deliberately restricted their focus to a single gender to avoid introducing a confounding variable (Zampeli et al, 2010; Tzagarakis et al, 2010; Nazary-Moghdam et al, 2019). One study specifically states gender as a confounder, due to females having a “lower complexity of movement” and having different movement patterns to males (Rathleff et al, 2013).

As the groups are heterogenous in terms of age and condition, this would also suggest that the weight of participants would also be variable. Taking the mean age and weight, the ACL studies consider a population that have a BMI over 25, which may be a confounding variable when considering the effect of the joint dysfunction on gait. In particular, increased weight has been linked to increased levels of disability in knee OA (Okoro et al, 2004) which suggests that this may be a factor here also, so participants have also been matched according to BMI as well as age in the control group.

In addition, other key study characteristics relating to the methodology and measures studied, test protocol and control group were extracted to examine key themes and identify gaps (Munn et al, 2018). In common with other scoping reviews, the overall quality of the study has not been used as an exclusion criterion but the quality score has been presented to give an overall picture of study validity and rigour (Littell et al, 2008). Relevant study characteristics relating to methodological quality have also been extracted for synthesis to gain an understanding of the development of the study protocols and the potential gaps in methodology (Munn et al, 2018; Littell et al, 2008).

The studies consider a wide range of measures, types of injury and activity, so a meta-analysis of the data would not be appropriate as the data is too heterogenous for this to be meaningful.

4. Discussion

4.1 Research groups

A number of studies have been produced using a similar core group of researchers (Stergiou et al, 2004a; Georgoulis et al, 2006; Moraiti et al, 2007; Zampeli et al, 2010), so show commonality of approach and measure, with later studies building on findings of earlier papers. This should be considered when assessing the choice of measure, algorithm and approach, as these have not necessarily been independently chosen, but instead developed from previous research and may include methodological bias. Stergiou and Decker have reviewed and synthesized the ACL studies from this group to pool their findings up to 2011 (Stergiou and Decker, 2011), and a recent study (Nazary-Moghdam et al, 2019) builds on these foundations.

In addition, one study (Mahmoudian et al, 2016) uses data from a previous paper (Yakhdani et al, 2010) to apply new techniques to evaluate local dynamic stability.

4.2 Statistics

Sample sizes were commonly small, which may relate to the availability and access to injured subjects, but this also limited the chance of obtaining statistically significant results as well as violating the assumption that the data were normally distributed. Non-parametric testing was used exclusively in two studies (Yakhdani et al, 2010; Terada et al, 2015), whereas in the studies using only parametric testing only two provide evidence of testing for the data being normally distributed (Tanimoto et al, 2017; Schütte et al, 2018) despite small sample sizes in most cases. In addition, a power analysis was only documented in five studies (Moraiti et al 2007; Tanimoto et al, 2017; Rathleff et al, 2011; Schütte et al, 2018; Rathleff et al, 2013) with one other justifying statistical power not being an issue due to the high number of significant results presented (Yakhdani et al, 2010). Power analysis was used to evaluate an appropriate sample size using 80% (Rathleff et al, 2011; Rathleff et al, 2013) and 90% (Schütte et al, 2018). Despite evidence suggesting observed power calculation is “conceptually flawed … [and] analytically misleading” (Zhang et al, 2019), posthoc power analysis was calculated in two cases (Moraiti et al 2007; Tanimoto et al, 2017) suggesting sample sizes were too low in each case (71% and 30% respectively).

In addition, non-linear measures tend to have small effect sizes (Mehdizadeh, 2018), as they tend to have a limited and narrow range of values with differences between injury and control groups therefore likely to be small. This further affects the significance of testing, and the sample size required in order to ensure statistically significant results.

Effect sizes are provided in four studies (Tochigi et al, 2011; Terada et al, 2015; Schutte et al, 2018; Nazary-Moghadam et al, 2019) and have been calculated where sufficient data has been provided (means and standard deviations) to do so, shown in Table 2 below.

Table 2: Effect sizes.

	Measure	Effect size (Cohen's d)
Stergiou et al, 2004a	LyE. Joint angles.	0.52 (calculated)
Moraiti et al, 2007	LyE. Joint angles.	0.70 (calculated from provided power figure)
Tzagarakis et al, 2010	Differential entropy Accelerometer.	Medio-lateral acceleration: 2.40 Anterior-posterior acceleration: 0.76 (calculated)
Nazary-Moghadam et al, 2019	LyE Joint angles	0.57 (provided).
Tochigi et al, 2011	SaEn. Accelerometer.	< 0.04 (provided)
Alkjaer et al, 2015	LyE and SaEn Joint angles and stride intervals.	SaEn stride intervals: 0.91 LyE ankle: 1.09 LyE knee: 1.00 (calculated)
Tanimoto et al, 2017	Fractal scaling exponent. Accelerometer.	Angular velocity: 0.10 Stride time: 0.17 (calculated)
Schutte et al, 2018	SaEn. Accelerometer.	Vertical acceleration: 0.50 Medio-lateral acceleration: 0.33 Anterior-posterior acceleration: 0.53 (provided)
Terada et al, 2015	SaEn. Joint angles.	< 0.04 (provided).

4.3 Control subjects

Two of the ACL studies (Stergiou et al, 2004a; Georgoulis et al, 2006) used the contralateral leg as the control to compare the injured side to the unaffected side to measure variability, but have suggested that the contralateral side is also affected by the injury, either due to compensation or adaptations due to injury. Later studies (Moraiti et al, 2007; Zampeli et al, 2010; Tzagarakis et al, 2010; Nazary-Moghdam et al, 2019) have used a healthy control population to compare with both affected and contralateral joint in the ACL deficient participants.

The studies considering other types of injury used age matched healthy individuals, including one study which used a slightly younger population but checked that this was not statistically significant (Tanimoto et al, 2017). One study used a wide range of ages in the control group 21-79 years in order to also evaluate changes in variability with age, but restricted analysis to an age matched control group within this (Tochigi et al, 2011).

4.4 Equipment

The studies include a range of different equipment, using motion capture, accelerometry and goniometers, with a range of different surfaces considered also, this is summarized in Table 3 below (shaded to show common injury focus).

Table 3: Study equipment and methods.

	Injury	Equipment	Measure	Methodology
Stergiou et al, 2004a	ACL	6 motion capture cameras 50Hz 15 markers	Unfiltered knee angular displacement	Self-selected speed, treadmill, ±20%
Georgoulis et al, 2006	ACL	6 motion capture cameras 50Hz 15 markers	Unfiltered knee angular displacement	Self-selected speed, treadmill, ±20%
Moraiti et al, 2007	ACL	6 motion capture cameras 50Hz 15 markers	Unfiltered knee angular displacement	Self-selected speed, treadmill.
Zampeli et al, 2010	ACL	8 motion capture cameras, 100Hz, 16 markers	Unfiltered knee angular displacement	Self-selected speed, treadmill, walking backwards.
Tzagarakis et al, 2010	ACL	Triaxial 12-bit digital output linear accelerometer sensor	Accelerometery.	Self-selected speed, 40m indoor.
Nazary-Moghadam et al, 2019	ACL	5 motion capture cameras, 100Hz, 15 markers.	Three-dimensional angular displacement of the knee joint	Treadmill, self-selected ±20%
Yakhdani et al, 2010	Knee OA	LED motion capture.	Angular velocity sagittal knee movement.	Treadmill, fixed speeds 0.6 km/h to 5.4 km/h (in increments of 0.8 km/h).
Tochigi et al, 2011	Knee OA	Inertial measurement unit.	Acceleration as 3d vectors.	400m self-selected speed, plus as fast as possible, indoor.
Alkjaer et al, 2015	Knee OA	Goniometers	Joint angles – filtered.	Fixed speed, treadmill walking
Mahmoudian et al, 2016	Knee OA	LED motion capture.	Angular velocity sagittal knee movement.	Treadmill, fixed speeds 0.6 km/h to 5.4 km/h (in increments of 0.8 km/h).
Tanimoto et al, 2017	Knee OA	Accelerometer	Peak shank angular velocity. Stride time.	Self-selected speed, treadmill.
Rathleff et al, 2011	MTSS	Video capture	Dynamic navicular drop.	Self-selected speed, treadmill.
Schutte et al, 2018	MTSS	Accelerometer	Trunk triaxial acceleration.	Continuous maximal effort fatiguing outdoor run of 3200 m.
Rathleff et al, 2013	PFPS	Goniometer	Joint angles.	Stair descent, 2x12, self-selected speed.
Terada et al, 2015	Chronic ankle instability	200Hz motion capture, 57 markers (clusters)	Sagittal and frontal joint angles ankle, knee, hip, trunk.	Self-selected speed, treadmill.

Motion capture cameras were most commonly used, with both passive (Stergiou et al, 2004a; Georgoulis et al, 2006; Moraiti et al, 2007; Zampeli et al, 2010; Nazary-Moghdam et al, 2019; Terada et al, 2015) and active (Yakhdani et al, 2010; Mahmoudian et al, 2016) marker sets. Passive systems are considered to be more accurate than active systems (van der Kruk and Reijne, 2018), and may also be more appropriate for the large data volumes captured (Begg and Palaniswami, 2006). Within these studies, one used clusters of markers for increased accuracy (Terada et al, 2015) whereas the others used the standard Helen Hayes marker set. All of the motion capture studies restricted their focus to sagittal angles, looking at flexion/extension only, with the majority of the studies only looking at the knee joint (Stergiou et al, 2004a; Georgoulis et al, 2006; Moraiti et al, 2007; Zampeli et al, 2010; Nazary-Moghdam et al, 2019; Yakhdani et al, 2010; Mahmoudian et al, 2016) and one considering ankle, hip and trunk in addition (Terada et al, 2015).

Capture frequencies varied from 50Hz to 200Hz, with this increasing with year of publication, possibly suggesting improvements in technology and data manipulation over this time. Capture frequency is an important consideration when considering data capture for non-linear analysis, as the sampling frequency needs to be high enough to capture the quickest system changes – the minimum frequency should be double that of the fastest change due to the Nyquist sample theory, with 24Hz recommended for walking trials (Myers, 2017). However, a high sample frequency can also introduce noise to the data which can give misleading results. It is common to use a sample size 5-10 times the highest frequency (Myers, 2017) which is consistent with the larger values in these papers, but this may also suggest that these studies are at increased risk of oversampling and therefore error due to noise in the time series.

The remaining papers considered EMG to measure muscle activation variability (Alkjaer et al, 2015; Rathleff et al, 2011; Rathleff et al, 2013) with movement variability evaluated by measuring joint angles via goniometers (Alkjaer et al, 2015; Rathleff et al, 2013) or average navicular drop (Rathleff, 2011). Further papers considered accelerometry data (Tzagarakis et al, 2010; Tochigi et al, 2011; Tanimoto et al, 2017; Schütte et al, 2018). Despite the range of methods and measures evaluated, there is little justification for the choice of technology used or the measure analysed, with only one study justifying the use of accelerometry data as a cheap, easy and accessible method (Schütte et al, 2018).

The majority of the studies focused on treadmill walking (Stergiou et al, 2004a; Georgoulis et al, 2006; Moraiti et al, 2007; Zampeli et al, 2010; Nazary-Moghdam et al, 2019; Yakhdani et al, 2010; Alkjaer et al, 2015; Mahmoudian et al, 2016; Tanimoto et al, 2017; Rathleff et al, 2011; Terada et al, 2015), with two indoor walking studies (Tzagarakis et al, 2010; Tochigi et al, 2011), one indoor stair descent (Rathleff et al, 2013), and one considering outdoor running (Schütte et al, 2018). One issue identified is the ecological validity and lack of transferability of treadmill studies to overground walking. Despite linear measures not being affected when comparing overground and treadmill walking, treadmill walking can affect local dynamic stability and non-linear analysis of gait (Dingwell et al, 2001; Terrier and Dériaz, 2011). However, studies also suggest that variable speed is also a factor that may affect the stability of the gait pattern (Stergiou et al, 2004a) and many focus on the importance of maintaining a fixed speed, which can only reliably be done using a treadmill (Moraiti et al, 2007; Nazary-Moghdam et al, 2019; Tanimoto et al, 2017).

Most studies use a self-selected walking speed to remove any effects of speed as a confounder (Moraiti et al, 2007; Zampeli et al, 2010; Tzagarakis et al, 2010; Tanimoto et al, 2017; Rathleff et al, 2011; Rathleff et al, 2013) or maximal speeds (Tochigi et al, 2011; Schütte et al, 2018). Some studies use fixed speeds (Yakhdani et al, 2010; Alkjaer et al, 2015; Mahmoudian et al, 2016) but it is not clear how this will affect the analysis done. Where studies attempt to identify if speed is a confounding variable, all three use ±20% (Stergiou et al, 2004a; Georgoulis et al, 2006; Nazary-Moghdam et al, 2019). One study found speed did not affect local dynamic stability (Stergiou et al, 2004a), but others found a significant correlation between speed and movement rigidity (Georgoulis et al, 2006) and speed and stability (Nazary-Moghdam et al, 2019) which suggests that this needs to be controlled and normalized over each patient to remove this effect from the measure evaluated.

When a paper was considering a specific aspect of gait, this was limited to show the effect of the injury at this point, so Rathleff et al (2013) only considered the stance phase of stair descent, as this was where the injury commonly caused pain. Yakhdani et al (2010) restricted attention to the part of the stride cycle that most usually related to falling, and this data was reanalyzed in Mahmoudian et al (2016). However, other studies restricted their focus due to common errors in capturing data in certain planes, so not including rotation (Tzagarakis et al, 2010; Terada et al, 2015) or only including flexion/extension data (Stergiou et al, 2004a; Georgoulis et al, 2006; Moraiti et al, 2007; Zampeli et al, 2010; Nazary-Moghdam et al, 2019; Yakhdani et al, 2010; Mahmoudian et al, 2016; Tanimoto et al, 2017), which fails to address the effects of injury in other planes of movement, with ACL injury in particular affecting rotation and overall joint stability (Quatman and Hewett, 2009).

4.5 Analysis method

Calculation of Lyapunov exponent or sample entropy were the most popular choices of non-linear analysis method, with one study using differential entropy (Tzagarakis et al, 2010) and one using a fractal scaling exponent (Tanimoto et al, 2017). One paper (Mahmoudian et al, 2016) analyses previously captured data (Yakhdani et al, 2010) using time-dependent local stability in addition to Lyapunov exponents, to evaluate how local stability changes within a stride cycle. Justification of choice of analysis method is not generally presented, and no rationale is given for use of one over another, although accelerometry data tends to use entropy, which may be due to previous studies having done so, rather than any methodological decision being made to choose this approach. There is some evidence that sample entropy has been used to confirm previous findings using Lyapunov exponents (Stergiou and Decker, 2011) and that these can be used together to gain information on both stability and regularity (Alkjaer et al, 2015).

When calculating Lyapunov exponents, embedding dimension (m) and time delay (τ) parameters are chosen to define the state space of the time series (Wurdeman, 2017). Choosing a time delay that is too small will limit the amount of useful information about how the dynamics of the system changes, but too large a value may result in missing data (Stergiou et al, 2004a). Similarly, the selection of embedding dimension to recreate the state space is important, as using an unnecessarily high embedding dimension will increase the effect of any noise in the data (Wurdeman, 2017), whereas having a dimension that is too small will hide characteristics of the time series, so it is important to select a dimension that contains the full characteristics representing the state space (Wurdeman, 2017). The parameters used in these studies are based on previous gait related studies with five-dimensional state space justified for use when calculating Lyapunov exponents (Stergiou et al, 2004), however while this may be appropriate for a healthy population, higher dimensions may be required to fully investigate populations with injury, as pathology may increase the random elements present in the gait pattern (Wurdeman, 2017). Each study that calculates Lyapunov exponents states that the embedding dimension is derived based on previous research via the false nearest neighbor algorithm and the time delay using an average mutual information algorithm (Stergiou and Decker, 2011). The Rosenstein algorithm is used more frequently in gait related studies (Mehdizadeh, 2018), but one study (Nazary-Moghdam et al, 2019) specifically mentions the use of Wolf's algorithm (Wolf et al, 1985) which has been shown to be more accurate for small data sets (Cignetti, Decker, and Stergiou, 2012).

When calculating entropy, a time series sequence is divided into shorter sections depending on the window length (m) and these are compared to see how similar they are to determine the randomness of the time series. In addition, a tolerance (r) is used to define an "allowable difference" (Yentes, 2017) when looking at similarity of each section. If the tolerance is too small then sections of the time series may be wrongly determined to be not similar, whereas too large a tolerance will give false positive results and determine similarity where none exists, thus losing actual characteristics of randomness within the series (Yentes, 2017). Within the studies considered, entropy calculations all use window length of 2 and tolerance of either 0.1 (Rathleff et al, 2011; Rathleff et al, 2013) or 0.2 (Georgoulis et al, 2006; Tochigi et al, 2011; Alkjaer et al, 2015; Schütte et al, 2018; Terada et al, 2015) standard deviations justified based on earlier studies (Stergiou et al, 2004; Richman and Moorman, 2000; Vaillancourt and Newell, 2000). Most studies measuring rigidity of movement consider sample entropy (Tochigi et al, 2011; Alkjaer et al, 2015; Rathleff et al, 2011; Schütte et al, 2018; Rathleff et al, 2013; Terada et al, 2015) which has been shown to be more accurate for small data sets (Yentes et al, 2012), with one study considering approximate entropy (Georgoulis et al, 2006). The Gait Evaluation Differential Entropy Method is used in one study (Tzagarakis et al, 2010) which does not depend on the tolerance.

Most studies do not filter or smooth the data, as this removes valid points from the time series, but three studies filtered data using 4th order Butterworth filters (Tanimoto et al, 2017; Rathleff et al, 2011; Rathleff et al, 2013). Filtering data may mask the true nature of the variability of the movement, as this can exclude outliers and potentially 'noisy' data which may actually be valid indications of movement variability and changes in regularity, and this can mask true biomechanical signals particularly when considering high-frequency data (Myers, 2017).

4.6 Study quality

Study quality was assessed using criteria relating to both clear statements of research aims and findings, valid protocols followed, and statistical validity, based on the criteria introduced by Littell et al (2018). Both authors independently scored each paper based on these criteria, with a zero representing a lack of consideration or discussion of a criterion, two meaning this is fully met, and one for a partial consideration. Limits of agreement were used to ensure that both reviewers were reliably scoring each paper. Each criterion used, and the overall score per criterion is presented in Table 4 below.

Table 4 : Overall study quality per criterion

Criteria	Mean	SD
Was the research question clearly stated?	1.93	0.25
Were the inclusion and exclusion criteria clearly stated?	1.23	0.73
Were the subjects in the study representative of the pathological population?	1.93	0.25
Were the main findings of the study clearly described?	1.97	0.18
Did healthy controls' age and gender match those of the pathological group?	1.53	0.73
Was gait variability well defined?	1.90	0.31
Was the test protocol clearly stated and uniformly applied to all participants?	1.80	0.41
Was the protocol appropriate to measure gait variability?	1.70	0.47
Was a sample size justification via power analysis provided?	0.37	0.72
Were potential confounders properly controlled in the analysis?	1.47	0.51

The clear limitation here for the majority of the studies considered is the lack of sample size justification, as discussed above. Some studies also failed to fully consider the potential confounding variables (such as speed, gender, BMI, for example) or to clearly state the inclusion or exclusion criteria.

When considering individual study quality, this improved over time, with more recent papers showing clearer explanations of methodology, and generally more rigorous approach in terms of justification of sample sizes and explanation of approach. As one study (Mahmoudian et al, 2016) reused data captured in an earlier paper (Yakhdani et al, 2010) then this also means that limitations of the original study in terms of lack of power analysis, as well as any issues with inclusion and exclusion must also be limitations of the follow up study, so the quality score given to this paper must be viewed with this in mind.

Study quality per paper is shown graphically in Figure 2 below.

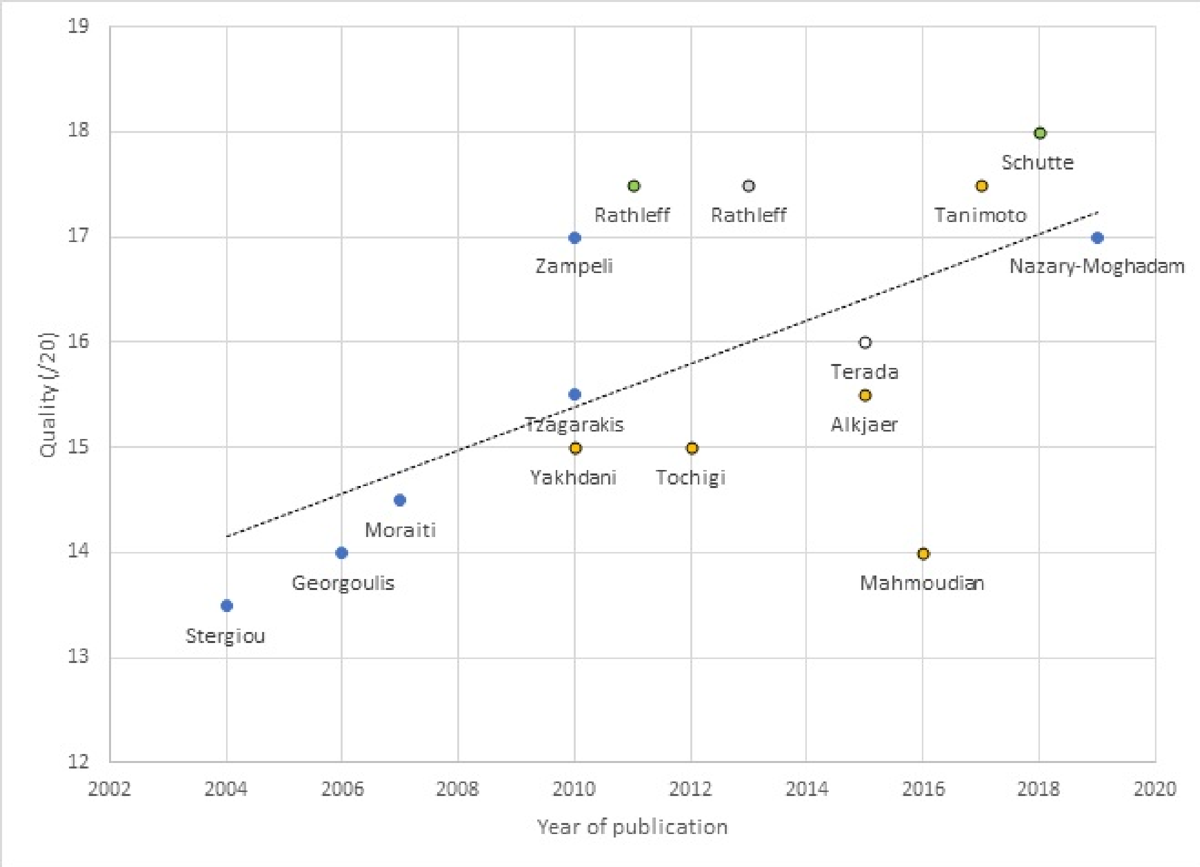

Figure 2: Individual study quality by year of publication

4.7 Findings

As explained above, gait may become more rigid as a result of injury, or more unstable and noisy (Stergiou and Decker, 2011), with a healthy gait pattern being somewhere between the two. Stability of a dynamical system relates to how sensitive the system is to the initial conditions, and is commonly evaluated with Lyapunov exponents, whereas rigidity and predictability of a system can be evaluated by calculating the entropy of the time series (Yentes, 2017).

Injury may cause increased rigidity compared with a healthy system, leaving it less able to adjust to changes (Georgoulis et al, 2006). This may also correlate with subsequent pathology, such as arthritis, following joint injury. This idea is supported by the results of studies of chronic ACL injury (Stergiou et al, 2004a; Georgoulis et al, 2006; Moraiti et al, 2007; Zampeli et al, 2010), knee OA (Yakhdani et al, 2010; Tochigi et al, 2011), PFPS (Rathleff et al, 2013) and chronic ankle instability (Terada et al, 2015) with increased stability and rigidity found in the injured group than the control group. Two studies identified no appreciable change between knee OA and control (Alkjaer et al, 2015; Tanimoto et al, 2017) but one of these suggests that stability may decrease with level of impairment (Tanimoto et al, 2017). No statistically significant difference was found in local stability of gait when considering MTSS versus healthy controls, but trunk movement rigidity was found to be affected by fatigue in the injured group, which also supports the idea of injury increasing stiffness of movement (Schütte et al, 2018).

One study shows significant decrease in rigidity in ACL deficient knees compared with control (Tzagarakis et al, 2010), but this study is focusing on acute rather than chronic injury which may account for this discrepancy as adaptation of gait may have occurred in the chronic case (Stergiou and Decker, 2011).

Dual tasking was considered in one study, which adds to the ecological validity of this methodology by making the test protocol more realistic, but no significant difference was found between the injured and healthy control group (Nazary-Moghdam et al, 2019), however this study did suggest that speed affects variability contradicting an earlier study (Stergiou et al, 2004a).

5. Conclusion

Stergiou and Decker (2011) have summarized the ACL studies included here up to 2011 and concluded that non-linear analysis of variability is useful in examining the functional outcome of any gait related disorder and determining rehabilitation programmes as well as interventions. Where injury has led to increased rigidity and increased regularity of movement, then there is evidence that introducing more variability into a rehabilitation programme may provide greater improvements in recovery and return to normal function (Dingwell and Cusumano, 2015) In addition, non-linear analysis may be a useful tool in medical assessment (Zampeli et al, 2010) and initial diagnosis (Terada et al, 2015).

As the evaluation of stability or rigidity relates to how mathematically chaotic or random a movement is, then a number of different measures have been used to evaluate the gait patterns, including joint angles, accelerometry data and muscle activation. These attributes may be applicable to a clinical laboratory setting but could also be analyzed easily in a sport or home setting via wearable technology to provide a cheap, easy alternative to gain valuable information on variability and repeatability of movement.

It is important to note that different results have been seen between chronic and acute injury conditions, and this may also have age and weight as confounding variables which has not yet been fully investigated. Despite using a range of methods, analysis has mostly been limited to the knee joint, and to sagittal movement of that joint, which are key limitations of these studies where injury is likely to affect other planes of movement. In addition, speed has been found to be a confounding variable, but there is lack of information on how this is standardized or how a self-selected speed is determined in order to reduce this affect.

Despite significant research on ageing (Mehdizadeh, 2018; Hamacher et al, 2011) and neurological conditions (Moon et al, 2016), the research on injury and how this affects variability is more limited, particularly when using non-linear methods, as is evident with only fifteen studies being selected for review here. The coverage of different injury is limited, with a main focus on ACL and arthritis, and expanding this to cover further joints and further planes of movement would help to tackle the current gaps in the literature. Further research in this area could improve diagnosis, interventions and treatment of injury and inform clinical decisions to ensure best practice within injury diagnosis and rehabilitation.

Recommendations for future research:

- Analysis using joint angle data has been restricted to sagittal angles due to errors in other planes. Future research aiming to minimize these errors, or identify more reliable methodological approaches, would allow analysis of variability in other movement planes and provide a more comprehensive measure of the level of movement variability due to injury.
- Papers considered in this review often had small sample sizes and many lacked a priori power analysis, which would improve the quality of the analysis. In addition, checking for normally distributed data to justify the statistical tests chosen and stating effect sizes would show a more rigorous mathematical approach.
- Justification of the choice of non-linear measure is often absent, and a clearer explanation of the selection of one measure over another to evaluate specific aspects of variability would contribute to existing knowledge in this area.A standardized methodology of selecting appropriate speed would exclude potential confounding variables, and would give further consistency and reliability to these study methods.
- While some types of injury have been considered in some detail, there are notable gaps when considering other lower body injury (for example, hip pathology) that would contribute to the overall understanding of movement variability due to injury.

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