Title: Texting while walking decreases local dynamic stability and variability

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SYNOPSIS: The following document contains the 10th semester submission of project group 17gr10207. Investigated over the course of the semester were the effects of smartphone use on walking in young, healthy adults. Included in the document, in order of appearance, are a main experimental manuscript and a supporting worksheet of the theory and workflow.

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Pages: [46]

Texting while walking decreases local dynamic stability and variability.

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Abstract

The aim of this study was to investigate the effects of smartphone use on the local dynamic stability while walking in young and healthy adults. To this end, 10 participants underwent repeated walking trials consisting of three conditions; 1) walking, 2) walking while texting, 3) walking while talking on a smartphone. In addition, to investigate the influence of walking speed, participants were instructed to undergo each condition at both a self-selected normal and self-selected fast walking speed. Data was gathered using a tri-axial accelerometer fixed at the lumbar level L4-L5. Local dynamic stability (LDS), defined by a maximum Lyapunov exponent (maxLyE), and gait variability, defined by standard deviation (SD) and coefficient of variation (CV) of stride time, and root mean square ratio (RMSratio), were assessed. The maxLyE increased significantly along the mediolateral axis, suggesting decreased stability in this direction when walking while texting compared to walking alone ($p<0.05$). Furthermore, the mean stride time decreased from self-selected normal speed to fast speed walking ($p<0.05$) and the variability in accelerations, as quantified by RMSratio along the mediolateral axis decreased significantly from walking while talking to walking alone ($p<0.05$). Similarly, significant decreases were observed for RMSratio of walking and texting at a fast speed to walking at a fast speed alone ($p<0.05$). These findings suggest that texting while walking decreases LDS and variability in the mediolateral direction in young, healthy, adults.

Keywords: Gait, Smartphone, Lyapunov, Accelerometer, Dual-task, Nonlinear.

Introduction

In recent years, the influence of smartphone use while walking has received considerable attention. [1–9] Recent reviews on the topic indicate that texting while walking produces alterations to critical gait parameters, such as; decreased walking speed, decreased step length, and increased double support time. [10] These alterations are suggestive of compromised balance and may serve as indicators of increased fall risk, although, due to varying methodologies, a consensus on the matter is difficult to achieve. [10,11] Methodological variations included walking conditions (over-ground or treadmill), varying measurement equipment, and varying secondary tasks. However, in the midst of this methodological variation some consistency has been present in the form of the dual-task paradigm, which has been central to these investigations. The paradigm allows for the assessment and comparison of the performance of a target task, or in other words, it compares the performance of a one task alone to that of two tasks at once; for example, comparing the performance of walking normally to walking while texting on a smartphone.[12,13]

As well as a standardisation of methodologies, new approaches to walking analysis can help in providing a full picture of the effects of smartphone use on walking. Nonlinear methods of analysis are one such relatively new technique to the field of biological science and gait analysis. Moreover, nonlinear analysis has been shown to be capable of distinguishing between young and elderly populations, as well as those with a history of falling and their non-falling counterparts.[14–17] Despite this, relatively few studies have used nonlinear techniques to investigate the effects of a dual-task scenario on the LDS of walking, and even fewer have done so with over-ground protocols.

LDS can be quantified using the maximum Lyapunov exponent (maxLyE), a frequently reported nonlinear measure in the investigation of walking stability (Table 1). The maxLyE provides the average rate of convergence or divergence of the local trajectories in the evolution of a time series. [18] It indicates the reaction of a dynamic system to small perturbations to the system providing information on the underlying dynamics of the system.[15,19] Theoretically, maxLyE requires data sets of considerable length to provide precise results, although this can be difficult to achieve in a laboratory environment without the use of a treadmill.[20,21] Issues therefore arise regarding the ecological validity as treadmill walking is thought to mask some of the underlying dynamics of gait.[22–24] Although promising, experimental studies using maxLyE consistently report that further research is required to fully understand the implications both from a conceptual perspective and in relation to functional walking.[18,25,26]

For a complete analysis of human gait the role of human motor control variability must also be considered. Movement variability may be an indication of a decrease in system performance or, contrarily, of a readily adaptable, functional, system - depending on the task under analysis. For example, when analysing repetitive movements, the presence of a more variable motor strategy can indicate a functional movement protecting from repetitive strain or injury.[27,28] However, many physiological systems show increased variability with aging that are indicative of decreased performance. [29,30] Therefore, to fully understand the effects of dual-task activities on gait, the integral dynamics and intrinsic variability of the system must be investigated.

Thus, the aim of this study was to analysis the effects of smartphone use while walking on the gait dynamics of young adults, using an over-ground-walking protocol. I hypothesized that increasing walking speed will increase stability in the anteroposterior direction, thereby decreasing maxLyE values, while decreasing stability in the mediolateral direction, thereby increasing maxLyE values, in line with the findings of previous research (Table 1). Moreover, I hypothesized that decreased LDS will be observed in the dual-task condition only when compared to walking without using a smartphone. Similarly, concerning variability, I hypothesized a decrease during a dual-task like walking while using a smartphone.

Materials & Methods

Participants

Twenty-two participants underwent gait analysis conducted at the AGIM laboratory, Grenoble, France. Of the 22 participants analysed, 12 were discarded due to a) incomplete data sets (due to organisational issues); b) unsuitable pathologies for the required analysis (e.g. rheumatoid arthritis, a history of spinal injury, and unequal limb length). The remaining 10 participants were healthy, young adults (7 males, 3 females; age = 24.7 ± 4.4 yrs.; height = 176 ± 5.4 cm; mass = 71.9 ± 12.2 kg), reported regular smartphone use, and possession of their current smartphone for longer than one month. None of the included participants had any neurological or physical disability that may interfered with gait. Finally, all participants provided informed consent prior to testing and ethical approval was attained from the University Grenoble Alpes.

Experimental protocol

Over the course of 12 walking trials, each participant completed two trials of the following conditions; 1) Normal walking, 2) Fast walking, 3) Normal walking while talking on a smartphone, 4) Fast walking while talking on a smartphone, 5) Normal walking while texting on a smartphone, 6) Fast walking while texting on a smartphone. The order of trials was pseudo-randomized and for each normal or fast walking trial, walking speed was self-selected. Pelvis accelerations were recorded using a tri-axial accelerometer (Physiolog 10D system, GaitUp, Lausanne, Switzerland; sampling rate 200Hz) tightly attached using strips of adhesive tape, at the level of L4-L5 spinous process. The inertial measurement unit measured accelerations along three axes; cranial-caudal (CC), antero-posterior (AP), and medio-lateral (ML). Participants were instructed to walk straight-ahead, along an 80-meter indoor corridor, at the speed designated (i.e. normal or fast). No smartphone holding instructions were provided before the talking or texting tasks, instead participants were simply instructed to begin with the smartphone in their hand and to respond to the smartphone notification if required. The auto-correct and predictive functions of the smartphone was disabled on all devices prior to testing. For this reason, participants completed three texting-familiarisation trials consisting of typing a standardised pangram before and in-between repeated trials. All texting questions were standardized between participants. Subsequent data analysis was conducted with Matlab R2015a (MathWorks, Natick, MA).

Table 1 - Participant demographic, healthy status, and summary findings related to maximum Lyapunov exponents of studies investigating gait using the Lyapunov method among their outcome measures. **λS** refers to the short-term Lyapunov exponent; **λL** refers to the long-term Lyapunov exponent. **LDS** refers to local dynamic stability; **OG** refers to over-ground walking; **TM** refers to treadmill walking; **UG** refers to uneven ground walking; **WOF** refers to walking without visual feedback; **WF** refers to walking with visual feedback; **PWSEC** refers to preferred walking speed with eyes closed; **SDD** refers to standard deviation of the difference; **SEM** refers to standard error of the mean; and finally, **ICC** refers to intra-class correlations.

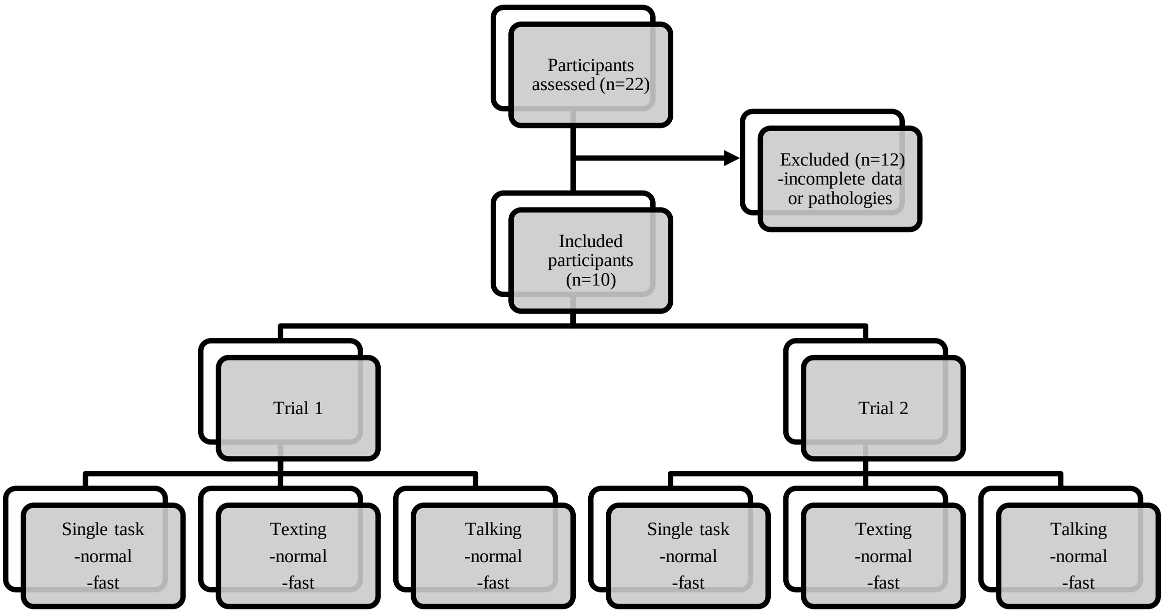
	Sample size	Health status	Age profile	Gender	Age(years)	Findings
			Y-young, O-older	M-male, F-female		
Bruijn et al. 2009[31]	15	Healthy	Y	4M:11F	23.6 ± 2.9	Walking speed had effects on λS and λL maxLyE. In the AP direction λS decreased as speed increased, while λL increased for speeds up to 1.5m/s. For the ML, λS showed an inverted U-shape pattern, while λL decreased with increasing speed. Both increased markedly in the vertical direction with increasing speed. Additionally, higher λS values corresponded with higher variability.
Bruijn et al. 2009[20]	9	Healthy	Y	9M:0F	25.5 ± 3.6	The ideal number of strides for investigating a complete Lyapunov series is greater than 150 strides but this is dictated by what specific aspect of gait is being investigated. Walking speed appeared to have a significant effect on stability even using short data sets. A fixed number of strides should be used.
Bruijn et al. 2010[32]	9	Healthy	Not reported	9M:0F	Not reported	Λs and λL values can be reliably measured by inertial motion units. Further studies are required to investigated LDS in real-life situations. Additionally, walking speed had a significant main effect on λS and λL, producing decreased λS and increased λL values with increasing walking speed. Correlation coefficients of 0.87 and 0.98 for were observed for λS and λl respectively.
Bruijn et al. 2010[33]	11	Healthy	Y	11M:0F	27.3 ± 3.3	Lower values were observed for λS with increasing walking speed. On the other hand, λL showed higher values with higher walking speeds.
Buzzi et al. 2003[14]	20	Healthy	O & Y	0M:20F	YA: 25.1 ± 5.3; OA: 74.6 ± 2.55	Portrayed by higher maxLyE, the fluctuation in the measured parameters are deterministic rather than random indicating degradation in LDS with age. Future studies need to investigate the sensitivity and specificity of nonlinear measures.
Cignetti, Decker & Stergiou 2012[34]	14	Healthy	O & Y	9M:5F	YA: 25 ± 4.86; OA: 70.28 ± 5.08	MaxLyE was closer to the expected value when the attractor is unfolded and when a larger number of data points are considered. Wolf's algorithm and Rosenstein's algorithm overestimated and underestimated the maxLyE respectively. However, the Wolf algorithm was more sensitive to the differences in LDS between groups from small gait data sets.

Dingwell et al. 2001[22]	10	Healthy	Y	5M:5F	27.1 ± 3.25	Mean standard deviation of anteroposterior accelerations of the trunk were significantly greater for OG than TM. Standard deviations were significantly greater for OG in lower limbs, thus TM walking significantly reduced kinematic variability. Trajectory divergence was significantly reduced for TM with significant reductions for λS and λL, thus more locally stable movements.
England & Granata 2007[35]	19	Healthy	Y	6M:13F	22.5 ± 2.8	Based on maxLyE, stability increases linearly with speed. The mean value for maxLyE was 1.08 ± 0.35 mm/s at the ankle, 1.40 ± 0.37 mm/s at the knee and 1.27 ± 0.34 mm/s at the hip. The maxLyE was significantly less at the ankle than the knee, or hip. The value at the hip was also significantly less than at the knee. Dynamic stability of walking is influenced by walking velocity with different contributions from ankle, knee, and hip joints.
Federolf, Tecante & Nigg 2012[36]	20	Healthy	Y	14M:6F	24 ± 2	There was significant difference maxLyE between walking in normal shoe and unstable shoe. The combination of PCA and Lyapunov exponents could distinguish between stable and unstable walking
Hamacher Hamacher & Schega 2015[37]	10	Clinical-abnormal gait due to joint pain	O	0M:10F	61 ± 4	A decrease in the maxLyE of pelvis; 1.47 ± 0.21 WOF to 1.88 ± 0.12 WF, and trunk 1.43 ± 0.18 WOF and 1.64 ± 0.12 WF velocity trajectories while subjects were walking with visual augmented feedback. Further investigation walking skills in challenging, controlled walking environments.
Hoogkamer et al. 2015[38]	32	Clinical – cerebellar patients & healthy	Y	8M:24F	H: 24.4 ± 7.3; C:24.4 ± 3.5	MaxLyE was higher in the patient group 1.72 ± 0.16 compared to 1.58 ± 0.14 healthy, as was step width (m) 0.21 ± 0.03 patient to 0.19 ± 0.02 healthy. MaxLyE values may be more sensitive to gait deficits than variability.
Howcroft et al. 2015[39]	11	Clinical – transtibial amputees	O	Not reported	61.78 ± 16.11	7 of the 26 measured parameters showed significant differences from LG to UG. Accelerations (m/sec^2): Vertical max decreased from LG 4.75 ± 1.56 to UG 1.88 ± 4.87; vertical range reflected this with a decrease from LG 7.82 ± 1.89 to UG 6.49 ± 1.77. Pelvis acceleration-derived parameters can differentiate between LG and UG walking. Future studies should expand research in relation to pelvis accelerometer derived output and fall risk.
Ihlen et al. 2012[19]	10	Healthy	Y	6M:4F	25 ± 4.7	Intra-stride transitions in LDS between single and double support might be important for the prognosis of gait function in older persons and clinical groups at risk of developing gait impairments.
Lockhart et al. 2008[15]	13	Healthy & fall-prone	O & Y	Not reported	HY:26.4 ± 2.3; HO:71.3 ±	MaxLyE for FE; HE and HY; 2.39 ± 0.32, 1.99 ± 0.08, 1.83 ± 0.19. Stability measures derived from nonlinear dynamics can be used to quantify the risk of falling. Further investigation into the use LDS as fall risk indicator.

					6.5; FO: 71.0 ± 3.0	
Miller et al. 2006[40]	6	Healthy	Y	Not reported	29 ± 7.4	Significant differences were found for maxLyE between the original and surrogate time series for both the Theiler algorithm a pseudo periodic surrogate algorithm.
Reynard & Terrier 2014[21]	100	Healthy	O & Y	50M:50F	44 ± 14	A substantial difference exists between estimates from 35 and 70 strides, differences amounted to +40%, +6%, and +8%; for long-term, stride and step maxLyE. Finally, the ML direction tends to exhibit lower SEM and SDD.
Reynard et al. 2014[17]	123	Clinical – central nervous disorder & healthy	Y	88M:55F	H: 44 ± 14; C: 40 ± 9	LDS can differentiate between healthy and non-healthy walkers, and potential correlation between LDS and cadence. ML gait stability was reduced by 33% in the patient group compared to the control group.
Russel & Haworth 2014[41]	10	Healthy	Y	6M:4F	21.1 ± 2.3	LDS was most stable at the preferred stride frequency of walking and decreased with faster and slower frequencies.
Son et al. 2009[42]	40	Healthy	Y	20M:20F	M 24.1 ± 3.1; F 22.5 ± 3.2	Significant differences were found in maxLyE values of the ankle. The results of this study were intended to act as normative values.
Terrier, Luthi, & Dériaz 2013[43]	25	Clinical – chronic foot and ankle injuries	O	20M:5F	48 ± 16	Most substantial improvement in LDS was along the ML direction. Foot orthotics had a significant effect of reducing pain and increasing LDS. Future studies should work towards making LDS a practical diagnostic tool.
Terrier & Reynard 2015[44]	100	Healthy	O & Y	50M:50F	44.2 ± 14.1	LDS in the ML direction was significantly different between groups, 15% of the variance in ML was due to age. Future longitudinal studies following individuals over many years should be conducted to confirm whether LDS is a valid method for early identification of falling.
van Schooten et al. 2013[45]	20	Healthy	Y	Not reported	28.5 ± 3.3	The within session reliability of λS are good (ICC >0.7). On an individual level, only substantial changes may be indicative of meaningful effects on LDS. Fixed delays and embedding dimensions for state space reconstruction yielded the best within- and between session test-retest reliability, as well as smallest SDD.
Kang & Dingwell 2006[16]	20	Healthy	Not reported	Not reported	Not reported	All divergence curves parameters were significantly greater during walking. None of the correlations between walking and standing mean divergence parameters were statistically significant, therefore LDS of standing did not predict that of walking.

Kang & Dingwell 2009[46]	35	Healthy	O & Y	24M:11F	YA: 23.3 ± 2.6 OA: 72.1 ± 6.0	Both λS and λL increased with speed, furthermore, higher values were observed for elderly subjects. Future research should investigate the role of neural noise in the brain and motor function of older adults.
Nessler et al. 2009[47]	14	Healthy	Y	9M:5F	23.33 ± 5.06	Significant differences were found for λL (4-10) exponents between solo and forced condition, no significant difference was found for the λS in either condition.
Reynard & Terrier 2015[48]	100	Healthy	O & Y	50M:50F	44 ± 14	Participants did not exhibit any significant changes in trunk acceleration variability. Interestingly, PWSEC brought about higher divergence for λS but lower divergence components for λS.

Figure 1 - Overall progression of the experimental protocol. Single task refers to walking only with no smartphone use. The order of the tasks was pseudo-randomized for 'Trial 1', and subsequently repeated in 'Trial 2'.



Pre-processing of data

To remove the effects of gait initiation and termination as well as to account for varying recording lengths, data were cut to 40 seconds per trial. To further ensure comparable trials, a uniform number of strides (N = 35), located in the midsection of the 40 seconds of the selected data, were selected for analysis. A single stride was defined as the time between subsequent heel strikes of the same limb, meaning every third CC acceleration peak denoted a single stride. Small measurement errors may exist in measured acceleration data as the measurement axes may not align with the horizontal-vertical coordinate system. By decomposing the acceleration signal into its static gravity and dynamic velocity component, it is possible to remove the confounding effects of both the gravity measurement and accelerometer orientation using simple trigonometric computations[49], so, to account for placement of the sensor, data was converted accordingly.

Local dynamic stability

The study of LDS assesses the capabilities of a system to adapt to small perturbations, indicating the stability of the system. The use of Lyapunov method offers quantification of this stability/instability by means of a maximum Lyapunov exponent (maxLyE). Higher maxLyE values representing lower stability. Continuous gait analysis produces time-series data, describing the dynamics of the system over time. To fully investigate a given time series, it must first be fully unfolded or represented in the highest appropriate dimension, reflecting the full dynamics of the system in state-space. Reconstruction of this state space involves calculating the appropriate embedding dimension and time lag. Taken's theorem proposes that a dynamic system can be portrayed by analysing a number of time 'lagged' copies of a single variable[50]. The appropriate number of dimensions for embedding was obtained by identifying false nearest neighbours, using global false nearest neighbour (GFNN) analysis, while the appropriate time delay was established using the average mutual information (AMI) analysis. Based on the findings of van Schooten et al. (2013), a fixed time delay (average across all trials) and a fixed embedding dimension (average across all trials) were used to assess the maxLyE along each axis to enable within subjects and trials comparisons[45]. To assess whether nonlinear analysis techniques were appropriate for the measured data, a number of surrogate data sets were generated. For each trial 19 surrogate data sets, of identical mean and standard deviation as the original data set, were created and the maximum Lyapunov component for each calculated. The embedding dimension for each surrogate data set was chosen as the average embedding dimension of the corresponding measurement axis of the original data set. Subsequently, a rank-order-test was conducted to assess the null hypothesis. In this case, the null hypothesis was that the dynamics of the times series were the result of a linear, stochastic process.

Gait variability
Mean, standard deviation, and coefficient of variation of stride time were calculated for each trial. Stride time was defined as the time between subsequent heel strikes of the same limb. Additionally, the root-mean-square ratio (RMSratio) of the ML pelvic accelerations were calculated. Given the variation in walking speed required for the current study, a normalization method recently introduced was employed.[51]

For each sample *n*, the 3D acceleration (x, y, z) vector norm was computed (Vec_n)

$$Vec_n = \sqrt{x_n^2 + y_n^2 + z_n^2}$$

and then the RMS of the norm:

$$T_{RMS} = \sqrt{1/_N \sum_{n=1}^{N} (Vec_n)^2}$$

Where T_{RMS} is the RMS of the vector norm and Vec_n the vector norm for each 3D acceleration. Once the procedure is repeated for the ML axis giving ML_{RMS}, the RMSratio can be computed as ML_{RMS}/T_{RMS}, therefore as a proportion of the total acceleration variability.

Statistical analysis
A Kolmogorov-Smirnov test for normality was conducted on the analysed data. Non-normal distributions underwent log transformation and were subsequently assessed. The influences of walking speed (self-selected normal or fast speed), trial number, and task (single task, texting, or talking) on the LDS were assessed by means of a three-way analysis of variance (ANOVA). As such, the dependent variables were maxLyE in the corrected CC, ML, and AP directions. To assess the measures of variability, both RMSratio and stride time, paired t-tests were used comparing the average participant values under each condition. The Bonferroni method for post-hoc comparisons were applied to assess the effects of task using a significance level of $p < 0.05$.

Results

Table 2 – The effects of smartphone use while walking; mean ± standard deviation of maximum Lyapunov exponents (maxLyE). Pelvic accelerations were measured along the cranial-caudal (CC), mediolateral (ML), and anteroposterior (AP) during each trial at a self-selected normal walking speed (SSW) and a self-selected fast walking speed (FWS). Walking variability was assessed by computing the RMSratio (Rr), the variability of stride time (ST), and coefficient of variation of stride time (CV).

	Walking only		Walking & Texting		Walking & Talking	
	SSW	FWS	SSW	FWS	SSW	FWS
maxLyE CC	1.47 ± 0.51	1.31 ± 0.38	1.60 ± 0.61	1.41 ± 0.41	1.33 ± 0.22	1.28 ± 0.30
maxLyE ML	1.72 ± 0.42	1.68 ± 0.42	1.99 ± 0.26*	1.94 ± 0.46*	1.87 ± 0.29	1.68 ± 0.29
maxLyE AP	1.95 ± 0.52	2.07 ± 0.37	1.95 ± 0.37	2.09 ± 0.52	1.85 ± 0.39	2.00 ± 0.72
Rr	0.11 ± 0.04	0.12 ± 0.04	0.11 ± 0.07	0.11 ± 0.04*	0.10 ± 0.04*	0.15 ± 0.10
ST	1.02 ± 0.14	0.92 ± 0.06	1.02 ± 0.11	0.96 ± 0.09	1.00 ± 0.08	0.93 ± 0.07
CV	0.13 ± 0.12	0.07 ± 0.05	0.11 ± 0.07	0.09 ± 0.07	0.08 ± 0.06	0.08 ± 0.06

*significantly different to the corresponding 'walking only' condition

Significant increases in maximum Lyapunov values were found in the ML direction ($p<0.05$), following post-hoc comparison, from the single task condition of walking to walking while texting on a smartphone. Furthermore, mean stride time significantly decreased with a change of speed from self-selected normal speed to self-selected fast speed ($p<0.05$). In addition, RMSratio decreased significantly from the single task condition to the walking while texting condition but only in the self-selected fast speed trials. A further significant decrease in RMSratio was observed from single task condition and self-selected normal walking speed while talking ($p<0.05$).

Discussion

The aim of this study was to investigate the effects of smartphone use during walking. In line with the hypotheses, decreased LDS in ML direction was seen, but only for a texting task and not a talking task. Regarding variability of walking, defined by root mean square ratio, standard deviation, and coefficient of variance of stride time, task had a significant effect on RMSratio for talking while walking at a normal speed, and texting while walking at a fast speed. Thus, in partial agreement with my hypotheses. In contradiction to the hypothesis, walking speed alone did not significantly affect LDS or variability. However, mean stride time did decrease significantly with increased walking speed.

Local dynamic stability during texting and walking

Lyapunov exponents provide the rate of convergence or divergence of neighbouring trajectories resulting from small perturbations.[18] An increase in a positive maxLyE value indicates an increasing rate of convergence and thereby an inability of the system to cope with small perturbations, i.e. decreased stability.[52] Interestingly, significant increases were only found when the participants were asked to walk while texting delineating that a dual-task like texting and walking alters the control of one of the most common activity of daily living. Aside from the recognized reductions in awareness for ones' surroundings and failure to properly address normal road safety conventions (i.e. assessing the risk of road-crossings), [2,4,5,53] texting while walking may also incur significant increases in the risk of falling by failing to interact with a changing environment.[7] This was shown to be the case with young adults, for whom the consequences of falling may be a minor problem, however, the consequences augment with pathology and age.[54]

Moreover, in agreement with previous research, we observed increased instability along the ML axis when investigating LDS.[17,21,31] In fact, previously when maxLyE were analysed across a wide range of age groups (20-69 years), only instability in the ML direction was reported to differ between groups and with increasing age.[44] Furthermore, when comparing healthy and fall-prone elderly participants, ML gait stability (given by maxLyE) was reduced by 33% in the fall-prone group.[17] These findings support particular attention to the investigation of LDS along the ML axis as an indicator of instability.

Contrary to previous findings, we did not report significant change in maxLyE values with increasing speed.[31,33] Reasons for this may lie in the methodological differences. In the current study, we opted for an ecologically valid environment. Participants were asked to perform over-ground-walking as opposed to treadmill walking. While still a topic for debate, it has been proposed that treadmill walking may mask some of the intrinsic characteristics of gait.[22-24] On the other hand, using a treadmill means that a much longer walking distance can be covered relatively easily, ensuring greater agreement with the theoretical basis of the implemented algorithm; another methodological difference between the studies. Furthermore, the speed of walking was largely chosen by the participants and so there were variations between participants (e.g. from 1.26m/s to 1.60m/s), in fact, the speed of walking depended not only on the participant's physical characteristics but also on their interpretation of 'walk at a fast/normal pace'. Finally, a large majority of the gait analysis using maxLyE have computed results using the Rosenstein algorithm.[55] In the present study, the Wolf algorithm was used as it has been shown to have fewer constraints when dealing with shorter data lengths.[34,50]

A few noteworthy aspects of the current protocol should be considered when interpreting the findings. For example, a minimum data length for gait analysis using the maxLyE of 150 strides has been proposed, whereas we use data of 35 strides length.[20] However, as portrayed by the wide variation in data lengths present in the literature (from 30 seconds to 60 minutes), this minimum length may not be representative (See 'Worksheet' table2(a)). Furthermore, while the method of generating surrogates used in the current study maintained the mean and variance of the original signal, the inter-cycle dynamics of a pseudo-periodic system such as walking may not have been fully preserved. Future studies should attempt the pseudo-periodic surrogate generation method used by Small et al. (2001).[51]

Strengths and limitations exist in every experimental design as the design of the research protocol is dictated by the research question, in this case, the effects of smartphone use on walking. As such, the implemented protocol was designed to mimic the daily activity of smartphone use as closely as possible by giving a small amount of instructions to the participant, using over-ground walking in place of treadmill walking, and covering a distance that was long enough to capture meaningful data but also of an appropriate length to remain ecologically valid (i.e. not too long as text messages are generally short). Furthermore, few studies had investigated the effects of smartphone use on the local dynamic stability of walking using Lyapunov exponents.

Variability of gait during texting and walking

A growing amount of experimental evidence points toward variability of gait providing critical insight into fall prediction, prevention, and gait stability.[26] In fact, recent review findings suggest stride-to-stride variations may provide a key insight into motor control and play a role in distinguishing between young and old test participants,[57,58] although this conclusion is not universal across experimental studies.[22] In the current study, variability was defined as the root mean square ratio along the mediolateral axis, as well as the standard deviation and coefficients of variation of stride time. Significant decreases in mean stride time were observed when walking speed was increased from normal walking to fast walking. Interestingly, no significant effect task was observed or any significant difference in standard deviation or coefficients of variation of stride time.

Root mean square of acceleration signal has been used previously to gauge the dispersion of acceleration signal relative to zero, in place of standard deviation.[59–62] However, this approach can be confounded by varying walking speeds, so recently a new method of comparing the ratio of RMS along an axis of interest to that of the total acceleration was introduced to solve this problem,[51] which has subsequently been implemented in more recent research.[44,48] In this study, significant decreases were found in RMSratio from walking while talking on a mobile to walking alone and in the fast walking speed condition, from walking while texting to walking alone. Since RMSratio may provide quantitative indices of gait abnormality when the ratio differs from that of a self-selected walking speed,[34] changes in RMSratio may suggest an influence of a texting task in combination with increasing walking speed on the gait pattern. Although, this conclusion is difficult to definitively assert as the results were not significant across all trials.

Technical perspectives

Further research is required to validate the use and implications of maxLyE as an indicator of gait stability, although already it has shown some potential in distinguishing between healthy and patient groups, as well as, fallers and non-fallers.[14,15,17,52,53] Recent developments in the field of concussion identification among athletes have led to interesting innovations, in particular those using a smartphone's inbuilt accelerometer to quantify stability by means of postural control.[54] Intra-class correlation coefficients indicated moderate to good reliability (0.21-0.57) of this method in comparison to the 'gold standard' of a stationary force plate. Given slightly improved accuracy, it is conceivable that this technique could be applied using a local dynamic stability threshold (given by a maxLyE), applicable to fall prediction, as part of rehabilitation protocols, or even as an indication of potentially hazardous smartphone use like texting while walking. An application using the built-in inertial measurement units of smartphone could provide feedback when instability is detected, perhaps alerting the user of their fall risk, their progress in rehabilitation, or the risks involved with their current activity.

Conclusions

In summary, the findings suggest that texting while walking reduced local dynamic stability and variability in the ML direction in young, healthy adults. Further research is required to establish reliable threshold values or ranges that can be used and applied in clinical, sporting, and everyday settings. The development of LDS as a valid tool for gait assessment should be attempted across all age ranges to further our understanding of the underlying dynamics of gait.

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Supplementary Worksheet: Theory & Workflow

The purpose of this worksheet is to supplement the manuscript *'Texting while walking decreases local dynamic stability and variability'*. In the first chapter, some of the key concepts underlying nonlinear analysis and their application to human gait analysis will be introduced. The second chapter will contain a review of the current literature conducted with the aim of establishing the current 'best-practice' in the application of nonlinear analysis to human gait. It contains the operational definitions of the most frequently encountered nonlinear analysis techniques used in the reviewed papers, the findings of the reviewing process, and a brief discussion on those findings.

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Chapter 1 – Core concepts of nonlinear analysis

In the following chapter the principal concepts underlying dynamic systems, time series reconstruction, and time series analysis.

1.1 Dynamic systems and chaos

Linear analysis is conventionally used to understand the stability of a system to small perturbations, assuming constant equilibrium and interpreting the 'mean' as the desired behaviour.[1] Conversely, dynamical analysis is used to describe 'systems of elements' that alter with time, aiming to understand the complexity of their inherent variability. These analysis methods analyse the patterns present in data over time.[2] These dynamic systems may be deterministic or stochastic. Deterministic systems are those which can only have one possible outcome, provided the current conditions are understood, whereas a stochastic system has outcomes that will vary according to probabilistic processes.[1] A sub-category of dynamical systems contains nonlinear systems, and yet a further sub-category of nonlinear systems contains chaotic systems. There are three fundamental criteria for a chaotic system. Firstly, small changes in the initial conditions of the system will have a large effect on the outcome of that system. Secondly, the same state is never repeated within the system and, thirdly, the system must be clearly bounded.[3] Chaotic systems are an important consideration for nonlinear analysis as while all dynamic systems are not necessarily chaotic, all chaotic systems are nonlinear, [4] therefore the analysis of a chaotic system will require nonlinear analysis methods.

1.2 Self-organisation

When conducting nonlinear analysis, particularly when the analysis concerns biological systems, self-organization is another important concept. It provides an answer to the progression of a nonlinear system from one state of complexity to another, thereby allowing better understanding of these systems as they become increasingly complex. Another approach to viewing self-organization is as 'the organisation of complexity from simplicity',[1] where the behaviour of two elements of a system depend on the behaviour of a third element. The relevance of self-organisation lies in that it appears to rely on the nonlinear interactions between the elements of the system and can provide important understanding of a complex system's behaviour over time.[1]

1.3 Time series analysis

Once the system is understood, it can begin to be described. To fully describe a systems behaviour over time, an appropriate time series analysis is necessary. Simply put, a time series is a sequential list of numbers that measures a process over time.[5] Nonlinear time series analysis differs from linear analysis in that it assumes that observations are dependent on the history of the system, meaning that the value of the current point will depend strongly on the values of the previous points.[1]

Several considerations must be made in conducting the analysis of a times series, from length of data to the processing techniques. A 'rule-of-thumb' for assessing the length of the time series required for the analysis is that the length must be ten to the power of the number of dimensions of the system. However, while this may be optimal from a mathematical perspective, data sets of such length may not have high ecological validity, as is the case for an investigation into the effects of everyday smartphone use.[1,6]

A further consideration for time-series analysis is the sampling frequency used during data collection as this will have a large impact on the quality of the analysed data. While following the recommendations of the Nyquist Theory will provide a valid signal, a further rule-of-thumb for the nonlinear analysis of gait, is a sampling frequency of approximately five times the highest frequency of the signal.[1] Yet another consideration is filtering of the raw data. Selecting and applying the appropriate filter is standard procedure for conducting linear analysis, but when conducting nonlinear analysis, filtering may in fact remove some of the integral dynamics of the system as well as noise frequencies.[7,8] However, this should be judged on a case by case basis as the presence of intrinsic and extrinsic influencing factors may be higher for some data sets than others. Subsequently, once these factors have been accounted for, the construction of a state space presents the next challenge.

1.4 State space reconstruction

To thoroughly analyse a time series, its complete structure must be considered. This can be achieved through state space reconstruction. State space reconstruction allows us to view the true dimensionality of the time series in a higher dimensional space. To transform the simple time series into a higher dimension it must be embedded into the state space. Embedding refers to the process of fitting the time series into the state space. The embedding dimension is the exact number of dimensions required to achieve full representation of the time series data.[1]

Finding the correct embedding dimension is achieved through the identification of false nearest neighbours. A false nearest neighbour is a data point that appears to fit in one position when viewed in a lower dimension but, upon analysis in a higher dimension, this proves not to be the case. In other words, in a lower dimension this data point may appear to lie on a line with surrounding data points, but once analysed more thoroughly, it does not lie in line. These points are often called 'false neighbours' and can be identified by measurement of the straight-line distances between data points, ensuring that this distance is below a predefined ratio threshold.[9] An iterative process of identifying false nearest neighbours continues while moving to higher dimensions until the percentage of false nearest neighbours drops to zero. The dimension at which this occurs can be considered as the embedding dimension.

Reconstruction of a state space also requires the correct selection of a time lag. A time lag or delay ensures that an attractor is fully unfolded. An attractor is a set of points which are invariant under dynamics, and towards which neighbouring states asymptotically approach over the course of the movement.[1] Too small a time lag and the attractor is not fully unfolded and the structure is not correctly represented. Too large a time lag, and the state points will be spread throughout the state space. To ensure the choice of the correct time lag, the average mutual information technique can be used. This technique calculates the dependency or correlation among each data point and takes the average over the time series. This process is repeated for increasing time lags. The values of at each time lag are plotted against the mutual information, and the time lag at the first minimum point is selected as the appropriate time lag for reconstruction. The sequence and importance of these processes is reflected in the review below.

In summary, the application of nonlinear analysis method to a biological time series requires the observation of several critical processes to ensure that the time series data is accurately prepared before the analysis takes place. It requires an understanding of chaotic systems and the concept of self-organisation but perhaps most importantly, the correct selection of time delay, embedding dimension, and nonlinear analysis method in accordance to the core research question, must be ensured. Choosing the embedding dimension can be done using the 'Global False Nearest Neighbour tool and likewise, the time lag can be selected using the 'First Minimum of the Average of Mutual Information tool.

Chapter 2: Gait analysis using nonlinear techniques

In this chapter, the findings and subsequent discussion on the literature review are presented. The key words of *variability* OR *gait* OR *walking* AND *nonlinear dynamics* were used to compile a list of the relevant literature, which were subsequently filtered and analysed. First, the definitions of nonlinear techniques encountered over the course of the review are detailed – beginning with the most frequently encountered and moving to the least frequently encountered. In the second section of this chapter, are the review findings and discussion.

2.1 Definitions of nonlinear methods

Beginning with local dynamic stability, measured as the short-term (0 to 1 stride or 0 to 0.5 of a stride), and long-term (4 to 10 strides) maximum Lyapunov exponent (maxLyE) was reported in 32 of the 37 studies identified (Table 2a). Overall it was defined consistently throughout, with small wording variations between studies in the extent of the definition. In summary, LyE can be defined as measures of the rate at which nearby trajectories from a time series in state space diverge over time.[10] The use of LyE is applicable to pseudo-periodic systems. [11–13]In a broader sense, local dynamic stability was defined as the sensitivity of a dynamic system to infinitesimally small perturbations,[14,15] or more recently defined as how the neuromuscular system instantaneously responds to small perturbations.[16]

Orbital stability, defined as the maximum Floquet multiplier (FM), was reported in five experimental studies (Table 3). Several assumptions were emphasized concerning Floquet theory. Firstly, Floquet theory assumes strict system periodicity with limit cycle behaviour, thereby assuming that the motor dynamics of gait are controlled by a central pattern generator, functioning as a limit cycle.[13,17,18] FM portray the rate of expansion or reduction of perturbations to gait over subsequent cycle, or in other words, to what extent small perturbations grow or diminish over consecutive gait cycles.[13,18–20]

Three studies reported entropy outcome measures, approximate,[21] multiscale,[12,22] and Shannon entropy.[22] Approximate entropy provides an indication of the predictability throughout a data set.[12] It computes the probability that two sequences similar form observations will remain close on the next incremental comparison *m+1*.[21,23] Multi-scale entropy, performs a similar task but along multiple scales, six or more time-series, to identify irregularity in a time series.[12,22]

Two studies analysed the ratio of odd to even harmonics, as the portion of the acceleration signal that is in phase with the participants stride frequency[24] and provides an indication of how smoothly the trunk is controlled during walking, therefore, an indication of balance and coordination.[12]

Long range correlations were reported in just one study.[25] Specifically, the fluctuations in stride interval were investigated. Long range correlations assess gait under the assumption that variations are not random, and the subsequent variations depend on those that come before.[20] These correlations over a longer range can be identified by means of detrended fluctuation analysis, which quantifies their presence over a given time series.[10,20]

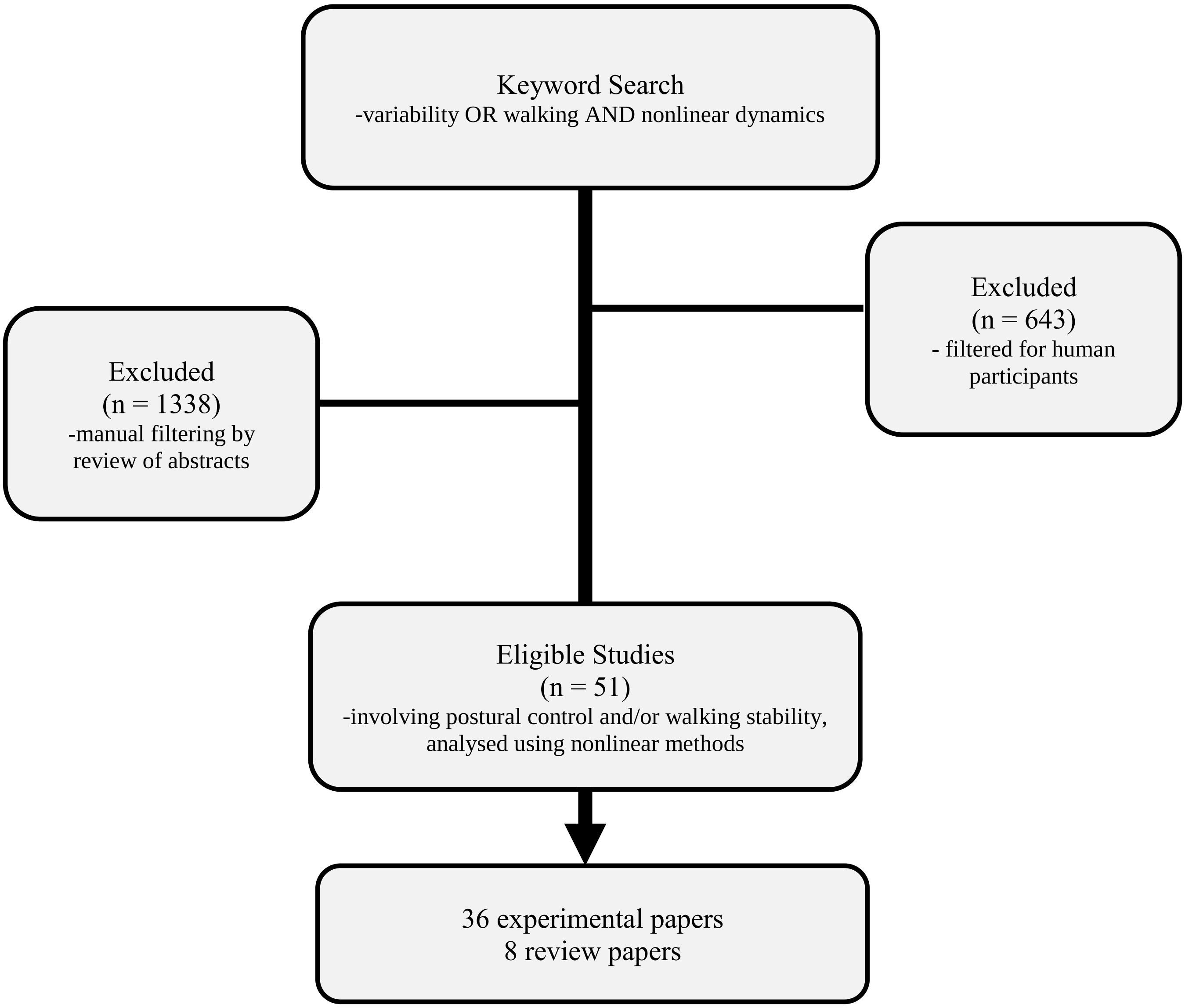
Finally, kernel based principal component analysis was implemented in one experimental study. Kernel principal component analysis is an attempt to maximally decorrelate data by dividing a data space into a linear combination of small bases consisting of orthogonal axes, with the aim of uncovering the nonlinear structure of the data.[26] On inspection of the reviewed gait literature, it is evident that some nonlinear analysis techniques have gained larger popularity. Predominantly, maximum Lyapunov exponents are used, either solely or in parallel with other nonlinear analysis techniques.

2.2 Review of the current literature

The aim of the following review is to identify the current 'best practice' in nonlinear gait analysis. The review will identify the most frequently reported techniques, methodological variations, and findings.

A web search was conducted using the PubMed Database. The key words variability OR gait OR walking AND nonlinear dynamics, yielded 2032 results. Following an additional filtering to include only human studies, the search produced 1389 results. Following a manual filtering based on titles, and subsequently abstracts, 51 papers were selected. All studies involved walking stability or postural control, analysed using nonlinear analysis methods or a combination of linear and nonlinear. Thirty-six experimental or observational studies and 8 reviews were identified.

Figure 1 - *Literature search and selection process..*



2.3 Experimental and observational studies

Thirty-six studies fell under this category, two of which were described as observational studies[11,25] Ten studies compared older adults to young adults,[15,19,26–33] and a further four studies examined older adults only.[11,22,24,34] Seven studies involved non-healthy or clinical populations[11,15,24,35–38] and sample sizes across all 36 studies ranged from 6 to 100. Interestingly, all reviewed studies were published between 2001 and 2017. (Table 1).

Tables 2a and 2b contain the methodological specifics of each study. As is evident from review of the tables, methodologies varied considerably, the number of trials per study varied from 1 to 10, as did the trial lengths (7.32 to 500m) and trial durations (30sec to 20mins). Furthermore, the number of strides analysed ranged from 20 to 300 strides, with 11 studies reporting stride numbers of greater than 100 strides (100-300 strides) and 11 studies reporting stride numbers less than 100 strides (20-75 strides). Twenty-four of the 36 studies used a treadmill protocol, while the remainder used over-ground protocols. Variations were also present in sensor placement, with 16 studies collecting at the trunk or pelvis, 12 collecting at the lower limb only (greater trochanter and down), 5 had a combination of lower-limb and pelvis or trunk, and 4 collected whole-body kinematic data (Table 2b). Trunk sensor locations were at the levels of thoracic vertebrae T6 to T8 or in some cases, at the base of the sternum[29,39] or 5cm below the sternal notch.[31,33] The majority of pelvic sensors were placed at the level of lumbar vertebrae L3-L5 (Table 2b), with one study reporting placement at the level of the sacrum,[24] and yet another study locating the sensor near the anterior superior iliac spine.[15] Additionally, one study reported placement of sensors on the shanks, 15 centimetres above the malleoli.[22]

Several data collection methods were used, the most frequent being inertial based sensors and optic camera systems, 14 studies using either method respectively (Table 2b). Other techniques involved light emitting diode active marker systems, foot switches, electro-goniometer, pressure sensitive walking path, and pressure insoles (Table 2b). Of note, pressure insoles were used in combination with inertial sensors.[34]

There exist several similarities and variations in the methods implemented in the reconstruction of the state space. Despite using similar methods to determine embedding dimensions and time delays, global false nearest neighbour and average of mutual information, embedding dimensions varied from 5 to 30[14,40] and time delays ranged from 10 to 25 samples.[41,42] Predominantly, Rosenstein's algorithm was used to estimate Lyapunov exponents, however, two studies used Wolf's algorithm[43] instead.[21,27] A recent study investigated the merits of both algorithms when investigating small data sets and found that both algorithms either overestimated (Wolf algorithm) or underestimated (Rosenstein)[44] the maximum Lyapunov value.[28] Despite this, and contrary to the trend of previous and current experimental work, the Wolf algorithm was recommended over the Rosenstein algorithm, when considering smaller data sets.[28] The correct procedure of data treatment was also unclear from review of the current literature, with 12 studies reporting data filtering, 6 studies not reporting the filtering process and 11 reporting using unfiltered data (Table 2a)

One study, aiming to assess the influence of state space reconstruction on the inter- and intra-day reliability of local dynamic stability, concluded that fixed embedding dimensions and fixed time delays provide the best within- and between-session test-retest reliability as well as the lowest smallest detectable difference.[16] In this case, best results were achieved using; a seven-dimension state space with a fixed time delay of six samples, or a nine-dimensional state space (analysing all three directions) with a fixed time delay of 24 samples.[16]

2.4 Effect of age

Investigations into local dynamic stability arise from the societal and individual effects of falling related injuries, particularly with a global population that is soon predicted to have a greater number of elderly than young individuals.[45] An understanding of fall risk and an ability to identify an individual with a high risk of falling are beneficial tools for clinicians, in a field where prevention is surely the best medicine. The findings of research on local dynamic stability suggest that nonlinear analysis of posture and gait may be promising as indicators of fall risk, although a strong correlation is yet to be established (See table 3).

Of the reviewed studies, 14 involved older participants (60 years or older), either exclusively or in comparison with younger participants. Among the findings of these investigations there are a few indicators of changes to gait dynamics because of age. For example, when compared to healthy, young controls, older adults were shown to have greater LyE values, and significantly greater coefficient of variation (CV) and standard deviations (SD) at the knee and ankle joints. [27]Subsequent studies have reported similar findings, when young and old, healthy adults were compared with a group of older participants who have a history of falling.[15] In this case, the fall-prone group also exhibited greater LyE values, indicating rapidly diverging dynamics, and therefore greater instability.[15] Furthermore, LyE were capable of distinguishing between fallers and non-fallers, although in a small sample.

So, what accounts for these changes in gait dynamics? Well, when the muscle activation (EMG amplitudes) of older adults were compared to those of younger adults, the older group displayed significantly greater EMG amplitudes. Findings that were in parallel with increased LyE short-term and long-term components.[19] This suggests that with aging, there is a decrease in the ease with which muscle activation patterns can respond to small perturbations from one stride to the next. Nonlinear analysis provides an indication of this continuous muscle activation, indicative of dynamic stability, that linear analysis cannot.[19] Additionally, larger cross-sectional studies have found nonlinear measures such as, mediolateral dynamic stability, portray differences between younger and older adults whereas, linear measures did not show change with age.[31]

Of note, are the similar findings of increased LyE values among clinical participants, who's pathologies have been identified to specifically inhibit gait such as cerebellar lesions, or lower limb paresis.[36,37] It suggests that not only can nonlinear analysis distinguish between clinical or older populations and their younger counterparts but that LyE may be a reliable indicator of instability that, based on further research, can lead to fall prevention.

2.5 Effect of speed and task

Just as age seems to be distinguishable through nonlinear analysis, walking conditions can also be identified. The effect of increasing or decreasing walking speed on local dynamic stability has been reported in several studies covered in the current review.[17,19,33,40–42,46–48] The finding of linear increases in LyE with walking speed would suggest that stability increases linearly with walking speed,[41,49] however, more recent studies have found contrary findings.[17,42] In this case, it appears that LyE short-term and long-term are differently affected by walking speed, short-term decreases with speed while long-term increases with speed.[17] A possible reason provided by the authors was the difference between the use of an equal number of strides at each speed, compared to an equal length of time at each speed.[17] Overall, the relationship between LyE and speed may not be so straightforward, and can strongly depend on the directional axis of choice. For example, along the anteroposterior axis, short-term LyE decreased with increasing speed, while long-term LyE increased.[46] While along the mediolateral axis LyE short-term has an inverted 'U' shape relationship with increasing speed, while long-term LyE decreases. Finally, along the vertical axis, both LyE components increase with speed.[46]

Aside for varying walking speed conditions, directional, sensory, rhythmical, and cognitive conditions were also investigated in the reviewed studies.[21,33,34,47,50] Compared to forward walking, backwards walking significantly increased maximum LyE values of the trunk in the anteroposterior and vertical directions.[47] Blindfolded walking was also investigated, however no destabilizing effects on gait were reported.[33] Of note in this case, the participants walked on a treadmill and in a controlled environment. Treadmill walking has been shown to produce significant decreases in short-term and long-term LyE compared to over-ground walking, indicating treadmill walking may be more stable. Therefore, visual occlusion may have a different influence in over-ground walking.[39] By designing methodologies using an over-ground walking protocol, the ecological validity of the results are improved. For example, if investigating the effects of smartphone use on the daily activity of walking, it would make sense to observe the behaviour in as natural an environment as possible to maximize the applicability of the findings.

With regards to variation of walking parameters such as stride time or frequency, enforced walking rhythm by means of metronomic beats did not influence the variation of stride frequency[21] but when conducted on a treadmill, walking alongside a partner treadmill (no metronome) significant increases in variability were observed for step length, knee, and ankle angles.[50] Only one study implemented a cognitive task, reporting centre of force path among their outcome measures.[34] A verbal fluency task – saying words beginning with specific prescribed letters A, F and S – reduced cadence, mean, minimum and maximum centre of force path, in combination with increasing stride time and stance time.[34] The addition of cognitive or physical tasks while walking has strong links to detrimental changes in spatiotemporal gait parameters, which may be further examined through nonlinear analysis methods.[51]

2.6 Discussion

The most commonly implemented nonlinear analysis measures encountered in the current review were Lyapunov exponents (LyE), outcome measure variability, and orbital stability based on Floquet theory. Their use is supported by some recent and less recent, reviews on the topic. When assessed from a validity perspective, both the short-term Lyapunov (LyE ST) exponents and measures of variability were determined to have the strongest support when investigating between group differences, followed by long-term Lyapunov exponents (LyE LT) and Floquet multipliers (FM).[20] While both LyE LT and FM have good construct validity, predictive validity remains weakly supported.[20] When looking at the ability to distinguish between groups, variability – in the form of SD of step width, stride time and CV of stride time – have been shown to be capable of distinguishing between older adults and younger adults.[52] The same has been demonstrated for LyE and FM, however with less consistency for the latter.[13,53] Variability as a functional aspect of gait has been acknowledged in the literature, with 'optimal' variability proposed to be a hallmark of healthy, functional gait.[10,54] The best clinical approach to analysing gait stability may be through combining variability analysis with that of nonlinear analysis, using both LyE ST and FM, covering both the aspects of periodicity and non-periodicity present in human gait. [55]

With regards to designing a methodology, it seems that over-ground walking yields more results more reflective of natural walking compared to walking on a treadmill, as the latter may significantly reduce the kinematic variability and potentially ‘mask’ the actual effect of task on locomotor control.[39] Additionally, a fixed number of strides should be analysed, particularly when manipulations of gait are in question, with the appropriate number of strides for accurate analysis thought to be in the region of 150 to 300.[40] Furthermore, to reduce Type II error repeated trials should be attempted.[40] However, the goal of the investigation plays a large role in the number of strides chosen and, while a stride number above a certain threshold may fulfil the mathematical models, it may not characterise an ecologically valid execution of the task.

Concerning state space reconstruction, a fixed time delay and embedding dimension are recommended.[54] The choice of the Rosenstein or Wolf algorithm depends on the length of the data set being analysed. A study conducted on the applicability of both algorithms concluded that for longer data sets, Rosenstein’s algorithm, is more appropriate whereas for shorter data sets, Wolf’s algorithm is recommended.[28]

In summary, walking speed may influence local dynamic stability but the effects of secondary tasks while walking remain unclear. Variability, as defined by standard deviation or coefficients of variation of stride time or stride width, of walking and perhaps some of the inherent characteristics of walking are reduced or masked by walking on a treadmill, so over-ground protocols are required if it improves the ecological validity. Variability of walking in the elderly may be a tool to distinguish the likelihood of falling, when used in combination with nonlinear analysis techniques such as the maximum Lyapunov exponent. The most recent literature calls for further investigation examining the potential of LDS as a tool for fall risk prediction,[11,15,31] for the expansion of research from treadmill walking into over-ground walking using inertial motion units.[24,34,47] Finally, there is a need for further examination of the effects on local dynamic stability when walking while performing multiple tasks at once.

Table 2 - Participant demographics, sample size, and healthy status from the reviewed literature investigating gait using nonlinear methodologies. **YA** = Young adults; **OA** = Older adults; **M** = Male; **F** = Female

	Number of participants	Health status	Age profile	Gender	Age (years)	Body mass (kg)	Body height (m)
		(Healthy, clinical, fallers)	(Young, older, young & older)	(Female / male)	Mean (SD)	Mean (SD)	Mean (SD)
Bruijn et al. 2009[46]	15	Healthy	Young	4M:11F	23.6 ± 2.9	66.7 ± 9.0	1.74 ± 0.08
Bruijn et al. 2009[40]	9	Healthy	Young	9M:0F	25.5 ± 3.6	77.9 ± 7.7	1.85 ± 0.08
Bruijn et al. 2010[17]	9	Healthy	Not reported	9M:0F	Not reported	Not reported	Not reported
Bruijn et al. 2010[42]	11	Healthy	Young	11M:0F	27.3 ± 3.3	75.5 ± 9.0	1.8 ± 0.06
Buzzi et al. 2003[27]	20	Healthy	Older & young	0M:20F	YA: 25.1 ± 5.3; OA: 74.6 ± 2.55	YA 63.9 ± 6.5; OA: 64.1 ± 9.69	YA: 1.70 ± 0.05; OA: 1.59 ± 0.05
Cignetti, Decker & Stergiou 2012[28]	14	Healthy	Older & young	9M:5F	YA: 25 ± 4.86; OA: 70.28 ± 5.08	YA: 69.9 ± 11.5; OA: 85.6 ± 13.5	YA: 1.76 ± 0.07; OA: 1.73 ± 0.08
Dingwell et al. 2001[39]	10	Healthy	Young	5M:5F	27.10 ± 3.25	64.9 ± 12.5	1.71 ± 0.09
England & Granata 2007[41]	19	Healthy	Young	6M:13F	22.5 ± 2.8	65.7 ± 12.7	1.7 ± 0.1
Federolf, Tecante & Nigg 2012[56]	20	Healthy	Young	14M:6F	24 ± 2	71 ± 11	1.77 ± 0.04
Hamacher, Hamacher & Schega 2015[35]	10	Clinical- abnormal gait due to joint pain	Older	0M:10F	61 ± 4	Not reported	Not reported
Hoogkamer et al. 2015[36]	32	Clinical – cerebellar patients & healthy	Young	8M:24F	H: 24.4 ± 7.3; C: 24.4 ± 3.5	Not reported	Not reported
Howcroft et al. 2014[34]	11	Healthy	Older	Not reported	76.2 ± 6.5	71.3 ± 13.7	1.67 ± 0.09
Howcroft et al. 2015[24]	11	Clinical – transtibial amputees	Older	Not reported	61.8 ± 16.1	85.8 ± 14.4	Not reported
Ihlen et al. 2012[14]	10	Healthy	Young	6M:4F	25 ± 4.7	74.5 ± 9.5	1.77 ± 0.08
Lockhart et al. 2008[15]	13	Healthy & 4 fall-prone	Older & young	Not reported	HY 26.4 ± 2.3; HO 71.3 ± 6.5; FO 71.0 ± 3.0	HY 71 ± 13.6; HO 71.2 ± 7.3; FO 88.6 ± 10.4	HY 1.77 ± 0.07; HO 1.65 ± 0.09; FO 1.72 ± 0.01
Miller et al. 2006[5]	6	Healthy	Young	Not reported	29 ± 7.4	67.7 ± 6.3	1.7 ± 0.05

Reynard & Terrier 2014[29]	100	Healthy	Older & young	50M:50F	44 ±14	70 ± 14	1.72 ± 0.07
Reynard et al. 2014[37]	123	Clinical – central nervous disorder & healthy	Young	88M:55F	44 ± 14; 40 ± 9	H: 71 ± 15; C: 69 ± 13	H: 1.70 ± 0.09; C:1.72 ± 0.08
Riva et al. 2014	51	Healthy	Young	Not reported	23 ± 3	Not reported	1.72 ± 0.01
Russel & Haworth 2014[21]	10	Healthy	Young	6M:4F	21.1 ± 2.3	75.8 ± 14.3	1.75 ±0.09
Segal et al. 2008[30]	19	Healthy	Older & young	14M:5F	44 ± 14	80 ± 17	1.70 ± 0.1
Son et al. 2009[57]	40	Healthy	Young	20M:20F	M 24.1 ± 3.1; F 22.5 ± 3.2	M 73.2 ± 9; F 52.7 ± 4.7	M 1.76 ± 0.05 F 1.61 ± 0.05
Terrier et al. 2013[11]	25	Clinical – chronic foot and ankle injuries	Older	20M:5F	48 ± 16	82 ± 15	1.73 ± 0.07
Terrier & Reynard 2015[31]	100	Healthy	Older & young	50M:50F	44.2 ± 14.1	70.2 ± 14.6	1.72 ± 0.07
van Schooten et al. 2013[16]	20	Healthy	Young	Not reported	28.5 ± 3.3	Not reported	Not reported
Wu et al. 2015[47]	17	Healthy	Young	17M:0F	24.9 ± 1.43	61.4 ± 6.1	1.70 ± 0.04
Beauchet et al. 2009[48]	29	Healthy	Young	15M:14F	28.3 ± 6.2	Not reported	Not reported
Hausdorff et al. 2001[25]	10	Healthy	Not reported	Not reported	Not reported	Not reported	Not reported
Kang & Dingwell 2006[38]	20	Healthy	Not reported	Not reported	Not reported	Not reported	Not reported
Kang & Dingwell 2009[19]	35	Healthy	Older & young	24M:11F	YA: 23.3 ± 2.6 OA: 72.1 ± 6.0	YA: 71.1 ± 9.86 OA:73.2 ± 12.3	YA: 1.73 ± 0.09 OA: 1.70 ± 0.1
Kurz & Stergiou 2007[58]	19	Healthy	Young	5M:14F	25.9 ± 5	67.87 ± 8.13	1.68 ± 0.06
Nessler et al. 2009[50]	14	Healthy	Young	9M:5F	23.3 ± 5.06	73.7 ± 19.76	1.74 ± 0.19
Bizovaka et al.2017[22]	139	Healthy	Older	Not reported	F:70.9 NF: 70.5	F:73.08 NF:73.99	F:1.60 NF:1.63
Stout et al. 2016[32]	20	Healthy	Older & young	YA: 2M:8F; OA4M;6F	YA:25.2 ± 1.5, OA 59.6 ± 10.7	Not reported	Not reported

Reynard & Terrier 2015[33]	100	Healthy	Older & young	50M:50F	44 ± 14	70.2 ± 14.6	1.72 ± 0.07
Wu et al. 2007[26]	48	Healthy	Older & young	Not reported	YA;25.1 ± 5.3 OA; 74.6 ± 2.55	Not reported	YA:1.73 ± 0.01 OA: 1.69 ± 0.09
Dingwell & Marin 2006[49]	11	Healthy	Young	Not reported	6M:6F	M: 29 ± 5.06; F: 24.4 ± 4.28	M: 81.14 ± 13.3; F:63.96 ± 12.15

Table 3(a) - Methodological variation including walking conditions, trial conditions, whether filtering was applied to raw data, and whether the studies involved Lyapunov exponents among the reviewed studies implementing nonlinear methods

	Treadmill use (Yes/No)	Number of trials	Trial length in meters	Duration in minutes	Filtered/Unfiltered data	Lyapunov method used (Yes/No)
Bruijn et al. 2009[46]	Y	5	Not applicable	3min	Unfiltered	Y
Bruijn et al. 2009[40]	Y	3	Not applicable	30min	Unfiltered	Y
Bruijn et al. 2010[17]	Y	3	Not applicable	5min	Unfiltered	Y
Bruijn et al. 2010[42]	Y	6	Not applicable	5min	Not reported	Y
Buzzi et al. 2003[27]	Y	1	Not applicable	30 (gait cycles)	Unfiltered	Y
Cignetti, Decker & Stergiou 2012[28]	Y	1	Not applicable	1-3min	Unfiltered	Y
Dingwell et al. 2001[39]	Y	2	200	10min	Not reported	Y
England & Granata 2007[41]	Y	4	Not applicable	30 (strides)	Filtered	Y
Federolf, Tecante & Nigg 2012[56]	Y	2	Not applicable	1min 40	Unfiltered	Y
Hamacher, Hamacher & Schega 2015[35]	N	1	20	5min	Not reported	Y
Hoogkamer et al. 2015[36]	Y	1	6	3min	Not reported	Y
Howcroft et al. 2014[34]	N	2	7.62	Not applicable	Filtered	Y
Howcroft et al. 2015[24]	N	10	10 & 8	Not reported	Filtered	Y
Ihlen et al. 2012[14]	Y	3	Not applicable	10min	Filtered	Y
Lockhart et al. 2008[15]	Y	1	Not applicable	1min	Filtered	Y
Miller et al. 2006[5]	Y	1	Not applicable	2min	Unfiltered	Y
Reynard & Terrier 2014[29]	Y	1	Not applicable	5min	Filtered	Y
Reynard et al. 2014[37]	N	2	70	0min 30	Filtered	Y
Riva et al. 2014	N	1	30	6min	Unfiltered	Y

Russel & Haworth 2014[21]	N	3	45.3	Not applicable	Unfiltered	Y
Segal et al. 2008[30]	Y	3	Not applicable	2-5min	Unfiltered	Y
Son et al. 2009[57]	Y	1	Not applicable	1min 30	Unfiltered	Y
Terrier et al. 2013[11]	N	4	70	0min 30	Unfiltered	Y
Terrier & Reynard 2015[31]	Y	1	Not applicable	5min	Filtered	Y
van Schooten et al. 2013[16]	N	4	500	Not reported	Not reported	Y
Wu et al. 2015[47]	Y	3	Not applicable	3min	Not reported	Y
Beauchet et al. 2009[48]	N	24	7.32	Not reported	Unfiltered	N
Hausdorff et al. 2001[25]	N	2	130	9mins & 60min	Not reported	N
Kang & Dingwell 2006[38]	Y	6	Not applicable	5min	Unfiltered	Y
Kang & Dingwell 2009[19]	Y	5	Not applicable	5min	Filtered	Y
Kurz & Stergiou 2007[58]	Y	1	Not applicable	2min	Unfiltered	Y
Nessler et al. 2009[50]	Y	3	Not applicable	2min 30 to 5min	Filtered	Y
Bizovaka et al.2017[22]	N	1	25	5min	Unfiltered	N
Stout et al. 2016[32]	Y	3	Not applicable	15min	Not reported	N
Reynard & Terrier 2015[33]	Y	3	Not applicable	6min	Filtered	Y
Wu et al. 2007[26]	N	3	10	Not reported	Filtered	N
Dingwell & Marin 2006[49]	Y	15	Not applicable	0min 30sec	Filtered	Y

Y = Yes; N = No

Table 2(b) - Methodological variations regarding the experimental constraints placed on participants, the testing apparatus used, and the placement of worn sensors or markers.

	Sensor position	Walking condition	Testing device(s) used
Bruijn et al. 2009[46]	Trunk	Participants walked at different speeds (from 0.62 to 1.72 m/s; at increments of 0.22m/s) on a treadmill	Active LED system (Optotrak Northern Digitial Inc, Waterloo, Ontario)
Bruijn et al. 2009[40]	Trunk	Participants walked on a treadmill under three different conditions (0.83, 1.38 m/s) and walking at 1.38m/s while attempting the Stroop test	Active LED system (Optotrak Northern Digital Inc, Waterloo, Ontario)
Bruijn et al. 2010[17]	Trunk	Participants walked on a treadmill at 3 different speeds (0.56, 1.12, and 1.68 m/s)	Infrared LED system (Optotrak Northern Digital Inc, Waterloo, Ontario); IMU (PI-node, Philips, The Netherlands)
Bruijn et al. 2010[42]	Trunk	Participants walked at three different speeds (0.56, 1.12 and 1.68 m/s) both with normal arm swing and arm swing restricted	Active LED system (Optotrak Northern Digitial Inc, Waterloo, Ontario) 2x3 camera array
Buzzi et al. 2003[27]	Lower limb	Participants walked on a treadmill at a self-selected pace, which was determined over a warm up of 8mins	Peak Performance Technologies Motus 4.0 system (Peak performance technologies inc, Englewood, CO, USA). Reflective markers, video taping
Cignetti, Decker & Stergiou 2012[28]	Lower limb	Participants walked on a treadmill with a safety harness (LiteGait, Mobility Research, LLC, Tempe, AZ), at their preferred walking speed.	EVART (Motion Analysis Corp, Santa Rosa CA)
Dingwell et al. 2001[39]	Trunk & lower limb	Participants wore standardized walking shoes, completed a 10-minute walking acclimatization on the treadmill. Overground walking trials were performed first, each participant walked along a 200m indoor walking track	DataLogger (Onset Computer, Inc, Pocasset, MA); Electro goniometers (Penny & Giles, Inc, Santa Monica, CA); 3D accelerometer (Kistler Instrument Corp., Amherst, NY)
England & Granata 2007[41]	Lower limb	Participants walked barefoot on a treadmill at 20%, 40%, 60%, and 80% of their PWS Froude velocity.	6 Camera (Vicon, Oxford Metrics) 240 HZ
Federolf, Tecante & Nigg 2012[56]	Whole body	Participants walked on a treadmill at a self-selected speed, on one occasion wearing a control sports type shoe (Ekiden 100, Kalenji, Decathlon SA., France) and in the other wearing an unstable shoe (Mwalk, Masai Barefoot Technology MBT, Switzerland)	8 Camer motion capture (Motion Analysis Corporation, Santa Rosa CA, USA); Eva Real-Time Software (EvaRT, Motion Analysis Corporation, Santa Rosa CA, USA)
Hamacher, Hamacher & Schega 2015[35]	Trunk & pelvis	Participants walked at their PWS for five minutes up and down a level hallway of (20m), of which 16(m) of walking were analysed.	MVN (Xsens); Head mounted display, Nikon Media Port UP300x); MovenStudio (v2.6, Xsens).
Hoogkamer et al. 2015[36]	Pelvis	Participants walked over ground at PWS over a distance of 6m followed by 3min of treadmill walking at 1.0m/s	Vicon Nexus, Oxford Metrics, Oxford, UK)100s/sec; Custom built instrumented treadmill, Forcelink, Culemborg, the Netherlands.

Howcroft et al. 2014[34]	Pelvis & lower limb	Participants completed a 7.62m walk with and without cognitive load. The cognitive load was a verbal fluency task requiring the participants to say words starting with A, F, or S in a randomized order	Pressure insoles (F-scan 3000E, Tekscan); 3D accelerometer (Gulf Coast X16-1C)120Hz
Howcroft et al. 2015[24]	Pelvis	Participants performed two walking scenarios; level-ground walking on a 10m walkway and simulated uneven ground walking on an 8m walkway covered by foam mats	Xsens accelerometer 100Hz; Xbus wireless unit (used to minimize skin movement)
Ihlen et al. 2012[14]	Lower limb	Participants performed three trials, following a familiarisation, at their preferred walking speed, -20%, and +20% of that preferred walking speed.	6 MX13 cameras 100Hz (Vicon Motion Systems, Oxford,UK)
Lockhart et al. 2008[15]	Pelvis & lower limb	Participants walked on a treadmill at PWS.	Dual axial accelerometer (ADXL 203; Analog Devices, Norwood, MA, USA) 125Hz; 6 camera Proflex system (Qualysis Medical AB, Gothenburg, Sweden; 120Hz)
Miller et al. 2006[5]	Lower limb	Participants walked at PWS for 2mins on a treadmill	Peak Motus optical capture system (Peak Performance, Centennial, CO)
Reynard & Terrier 2014[29]	Trunk	Participants walked (barefoot) on a level treadmill, at their PWS. This procedure was repeated between 10 and 14 days later.	3D accelerometer (Physiolog System, BioAGM, Switzerland) 200Hz
Reynard et al. 2014[37]	Pelvis	Participants walked, barefoot, at a PWS down a 70m long hallway for a period of at least 30 secs	Physiolog system (GaitUp, Lausanne, Switzerland) 200Hz
Riva et al. 2014	Trunk	Participants walked back and forth for 6mins along a 30m straight pathway, turning by 180 degrees at the end of each pathway	IMU FreeSense, Sensorize, s.r.l 200Hz and 100Hz
Russel & Haworth 2014[21]	Lower limb	Participants walked along a straight walkway, collecting sagittal plane knee motion, between two timing gaits. Participants walked at a prescribed frequency, dictated by a metronome attached at their waist.	Electrogoniometers (SG 150, Biometric Ltd, Cwmfelinfach, United Kingdom) 100 Hz; Brower Timing Systems, Draper, UT, Model Speed Trap II); Metronome (DM505, Seiko Sports Life Co., Tokyo, Japan)
Segal et al. 2008[30]	Whole body	Participants walked around a 1m radius circle at a constant walking speed, they then walked on a treadmill at PWS and at the same speed as the circle walking	12 camera Vicon 612 motion capture system (Lake Forest, CA) 250Hz; Vicon Plug-In-Gait model
Son et al. 2009[57]	Whole body	Participants walked at a PWS on a treadmill for 90s	8 camera motion capture (DCR-VX2100, Sony, Japan)
Terrier et al. 2013[11]	Trunk	Participants walked at PWS along a 70m corridor in both their own normal shoes, and orthopaedic shoes	3D accelerometer (Physiolog System, BioAGM, Switzerland) 200Hz; VAS visual analog scale
Terrier & Reynard 2015[31]	Trunk	Participants walked barefoot on a treadmill at 20%, 40%, 60%, and 80% of their Froude velocity.	3D accelerometer (Physiolog System, BioAGM, Switzerkand) 200Hz
van Schooten et al. 2013[16]	Pelvis	Participants walked back and forth over a straight outdoors footpath at PWS Measurements were done on two non-consecutive days, 2-30 weeks apart, resulting in two sessions of two walking trials	3D accelerometer (DynaPort MiniMod, McRobertsm Den Haag, The Netherlands) 100Hz

Wu et al. 2015[47]	Trunk & lower limb	Participants walked backward at PWS, forward walking at the same speed as BW, and FW at PWS	10 camera Vicon T40 3D Motion Capture (100Hz)
Beauchet et al. 2009[48]	Lower limb	Participants walked across a pressure sensitive electronic surface of 7.32*0.61m, at 80,70,60,50,40,30,20, and 10 percent of PWS. Verbal instruction was given to reduce speed by 10% before each trial. Participants had a 2m walk-up to the walkway	GAITRite Gold, CIR systems, PA, USA (80Hz)
Hausdorff et al. 2001[25]	Lower limb	Participants walked along a running track for 9 mins, and for 1 hour. In the latter case, participants walked at their usual slow and fast pace.	Ultra-thin force sensitive switches (not reported)
Kang & Dingwell 2006[38]	Trunk	Participants stood on a force plate or walked on a treadmill. Visual input was controlled by means of a blue screen placed in front of the participants. A harness was used to prevent falls	6 Camera (Vicon, Oxford Metrics) 60Hz
Kang & Dingwell 2009[19]	Trunk	Participants walked on a treadmill at PWS and increments of PWS (0.8-1.2 x PWS)	8 camera Vicon 612 (Oxford Metrics, UK)
Kurz & Stergiou 2007[58]	Lower limb	A horizontal actuator applied a forward horizontal force to the participant’s centre of mass via a cable spring system. Participants walked on the treadmill at a self-selected pace (1.01 (0.2) m/s), while a force was applied equal to 0%, 3%,6% and 9% of the participant's bodyweight.	4 Camera (Motion Analysis, Santa Rosa, California); Piezoelectric load cell (PCB Piezoelectronics Inc, Depew, New York)
Nessler et al. 2009[50]	Lower limb	Participants walked on a treadmill at (4.02km/h) under three conditions. Firstly, they walked by themselves at PWS. Secondly, they walked side-by-side with another participant on an adjacent treadmill. Finally, participants were instructed to purposely synchronize their walking	6 Camera (Vicon MX3+) 120Hz
Bizovaka et al.2017[22]	Trunk & Lower limb	Participants were divided into fallers and non-fallers by means of a self-reporting fall incidence. They then completed a Tinetti balance assessment, and walked over an indoor walkway.	3D accelerometers (Trigno wireless system, Delsys Inc, Natick MA USA) 296.3Hz
Stout et al. 2016[32]	Lower limb	Participants walked on a treadmill for each condition. During the free walking trial, PWS was determined and used for subsequent trials	8 Camera Qualysis motion capture (Gothenburg, Sweden) 200Hz; Visual 3D (C-Motion, Germantown, MD)
Reynard & Terrier 2015[33]	Trunk	Participants walked barefoot on a level treadmill wearing a safety harness. Three conditions, 1) walking at PWS eyes open, 2) PWS eyes closed, and 3) walking with eyes open at the walking speed selected for EC walking	Physiolog system (GaitUp, Lausanne, Switzerland) 200Hz
Wu et al. 2007[26]	Whole body	Participants walked, barefoot, along a 10m laboratory floor at PWS	Optotrak 3020 Motion analysis (Northern Digital Inc, Waterloo, Canada)
Dingwell & Marin 2006[49]	Trunk	Participants then walked a 60,80,100,120 & 140% of PWS	6 camera Vicon 612 infrared motion analysis system (Oxford Metrics, Oxford, UK)

PWS = Preferred walking speed; BW = Backward walking; FW = Forward walking

Table 4 -The findings of the reviewed research investigating gait using nonlinear methods among their outcome measures. **λS** refers to the short-term Lyapunov exponent; **λL** refers to the long-term Lyapunov exponent. **LDS** refers to local dynamic stability; **OG** refers to over-ground walking; **TM** refers to treadmill walking; **UG** refers to uneven ground; SDD refers to standard deviation of the difference; **SEM** refers to standard error of the mean; **ICC** refers to intra-class correlations.

	Findings
Bruijn et al. 2009[46]	Slow walking speed is not necessarily more stable than fast walking speed. Walking speed had effects on short-term (λS) and long-term (λL) Lyapunov exponents. In the anteroposterior (AP) direction λS decreased as speed increased, while λL increased for speeds up to 1.5m/s. For the ML, λS showed an inverted U-shape pattern, while λL decreased with increasing speed. Both increased markedly in the vertical direction with increasing speed. Additionally, higher λS values corresponded with higher variability. Therefore, walking dynamics are more accurately represented when analysed along each plane.
Bruijn et al. 2009[40]	The ideal number of strides for investigating a complete Lyapunov series is greater than 150 strides but this is dictated by what specific aspect of gait is being investigated. Walking speed appeared to have a significant effect on stability even using short data sets. A fixed number of strides should be used.
Bruijn et al. 2010[17]	Short-term (λS), long-term (λL) Lyapunov values, and maximum Floquet multiplier (Fmax) can be reliably measured by inertial motion units. Further studies are required to investigated local dynamic stability (LDS) in real-life situations. Additionally, walking speed had a significant main effect on λS and λL, producing decreased λS and increased λL values with increasing walking speed. Correlation coefficients of 0.87,0.98 & 0.66 for were observed for λS, λL &Fmax respectively.
Bruijn et al. 2010[42]	Lower values were observed for short-term (λS) with increasing walking speed. On the other hand, long-term (λL) showed higher values with higher walking speeds. Stride time (secs) decreased from ~ 1.8 to 1.2 and 1.0 at increasing speeds from 0.56, 1.12 & 1.68 m/s respectively. There were also significant reductions in stride-time variability (s) decreasing from 0.08 to 0.02 and 0.01 with increasing speed 0.56,1.12 and 1.68 respectively. Arm swing has no effect on local dynamic stability (LDS) in steady state gait but may be more appropriate for reacting to falls or large perturbations. Therefore, further investigations are required to investigate the effects perturbations in multiple directions as well as the effects of arm swing on recovery.
Buzzi et al. 2003[27]	Significantly smaller coefficients of variation (CV) and standard deviations (SD) were found between young and old for all parameters except for hip vertical displacement. Portrayed by higher Lyapunov values, the fluctuation in the measured parameters are deterministic rather than random indicating degradation in LDS with age. Elderly subjects showed decreased ability to adapt to stride to stride variations. Future studies need to investigate the sensitivity and specificity of nonlinear measures.
Cignetti, Decker & Stergiou 2012[28]	Maximum Lyapunov was closer to the expected value when the attractor is unfolded and when a larger number of data points are considered. Wolf's algorithm and Rosenstein's algorithm overestimated and underestimated the maximum Lyapunov respectively. However, the Wolf algorithm was more sensitive to the differences in local dynamic stability (LDS) between groups from small gait data sets. For small data sets use Wolf's algorithm, for larger set consider Rosenstein's

Dingwell et al. 2001[39]	Mean standard deviation of anteroposterior accelerations of the trunk were significantly greater for over-ground walking (OG) than treadmill walking (TM). Standard deviations were significantly greater for OG in lower limbs, thus TM walking significantly reduced kinematic variability. Trajectory divergence was significantly reduced for TM with significant reductions for λS and λL Lyapunov, thus more locally stable movements. Measures of stride-to-stride variability were poor indicators of local dynamic stability (LDS). In cases where differences in locomotor control are of interest, TM walking may mask some of the actual effects.
England & Granata 2007[41]	Variability in stride duration was observed despite walking at a constant velocity. Based on Lyapunov exponents, stability appears to increase linearly with speed. Stride time was significantly longer at 20% Froude velocity (1.57 ± 0.06) than 40% (1.12 ± 0.02), 60% (0.94 ± 0.01) and 80% (0.79 ± 0.02). The mean value for maximum Lyapunov exponents was 1.08 ± 0.35 mm/s at the ankle, 1.40 ± 0.37 mm/s at the knee and 1.27 ± 0.34 mm/s at the hip. The maximum Lyapunov exponent was significantly less at the ankle than the knee, or hip. The value at the hip was also significantly less than at the knee. Dynamic stability of walking is influenced by walking velocity with different contributions from ankle, knee, and hip joints. For future studies, a full set of Lyapunov exponents should be investigated, analysing multi-joint interactions to characterize dynamic stability of locomotion.
Federolf, Tecante & Nigg 2012[56]	For all subjects, principal components represented the same type of movement in both test shoe conditions. There was significant difference between walking in normal shoe and unstable shoe, therefore, the combination of principal component analysis (PCA) decomposition and nonlinear analysis could identify differences in temporal variability characteristics between the two conditions. The combination of PCA and Lyapunov exponents could distinguish between stable and unstable walking
Hamacher, Hamacher & Schega 2015[35]	A decrease in the maximum Lyapunov value of pelvis; (1.47 ± 0.21) without visual feedback (WOF) to (1.88 ± 0.12) with visual feedback (WF), and trunk (1.43 ± 0.18) WOF and (1.64 ± 0.12) WF velocity trajectories while subjects were walking with visual augmented feedback. Investigation walking skills in challenging, controlled walking environments and further investigation into the extent of increased fall risk provoked by visual feedback exceeds a possible increase in fall risk induced by a conventional gait-retraining intervention.
Hoogkamer et al. 2015[36]	Maximum Lyapunov was higher in the patient group (1.72 ± 0.16) compared to (1.58 ± 0.14) healthy, as was step width(m) (0.21 ± 0.03) patient to (0.19 ± 0.02) healthy. Lowest gait stability was correlated with patients with the largest vermal lesions, while mildly ataxic patients showed similar variability to healthy participants their gait stability was impaired. Maximum Lyapunov values may be more sensitive to gait deficits than variability, future studies should aim to gain more insight into the step widening and compensation characteristics of cerebellar patients.
Howcroft et al. 2014[34]	Minimum, mean, and median centre of force (COF) stance velocity all significantly decreased during dual-task walking (DT). Minimum COF velocity decreased by 18.77%, mean COF stance velocity decreased 7.83% and median COF stance velocity decreased 5.89%. Cadence significantly decreased (4.93%), while stride time (4.85%), stance time (6.78%), and swing time

	(2.27%) all increased during DT. The implemented devices could identify differences in gait between ST and DT walking in older adults. Further investigation of DT interference using IMU to assess fall risk.
Howcroft et al. 2015[24]	7 of the 26 measured parameters showed significant differences from level ground walking (LG) to uneven ground walking (UG). Accelerations (m/sec^2): Vertical max decreased from LG (4.75 ± 1.56) to UG (1.88 ± 4.88); vertical range reflected this with a decrease from LG (7.82 ± 1.89) to UG (6.48 ± 1.77). Temporal parameters of stride time (ST) and cadence (CAD) increased and decreased respectively (ST (s): 1.17 ± 0.065) LG to (1.37 ± 0.14) UG; CAD (steps/min) (1.42 ± 0.35) LG to (1.31 ± 0.22) UG. FFT (%) AP increased from LG (37.61 ± 9.56) to UG (56.16 ± 8.01) as did vertical LG (26.39 ± 6.52) to UG (42.17 ± 9.77). Finally, Harmonic Ratio increased for mediolateral (ML) from LG (0.29 ± 0.07) to UG (0.75 ± 0.14) Pelvis acceleration-derived parameters can differentiate between LG and UG walking in TTA with temporal, vertical acceleration and fast Fourier transform (FFT) first quartiles having the greatest distinguishability. Expand research in relation to pelvis accelerometer derived output and fall risk.
Ihlen et al. 2012[14]	Intra-stride transitions between convergence and divergence of state space trajectories were related to shifts between single and double support - these provide a time dependent Lyapunov exponent, giving the instantaneous state space divergences within a stride cycle. Intra-stride transitions in local dynamic stability (LDS) between single and double support might be important for the prognosis of gait function in older persons and clinical groups at risk of developing gait impairments.
Lockhart et al. 2008[15]	Average divergence of the fall-prone elderly group (FO) during initial step occurred much faster than that of healthy young adults (HY) and healthy older adults (HO). Group significantly influenced lye, 20% and 31% higher in the FO group than HO and HY groups respectively. Higher maximum Lyapunov values indicate more rapidly diverging dynamics and therefore, less stability. Furthermore, FO had a significantly shorter SL (45% to 52% shorter for HO and HY respectively. Also, significantly slower walking speed. Maximum Lyapunov exponents for FO; Ho and HY; 2.39 (0.32), 1.99 (0.08), 1.83 (0.19). Stability measures derived from nonlinear dynamics can be used to quantify the risk of falling. Further investigation into the use of local dynamic stability (LDS) as a fall investigator
Miller et al. 2006[5]	Significant differences were found for both maximum Lyapunov and approximate entropy (ApEn) values between the original and surrogate time series for both the Theiler algorithm a pseudo periodic surrogate algorithm.
Reynard & Terrier 2014[29]	A substantial difference exists between estimates from 35 and 70 strides, differences amounted to +40%, +6%, and +8%; for long-term, stride and step Lyapunov exponents. For 35 strides, significant difference between long-term and short-term local dynamic stability (ICC0.17-0.20; ICC0.71-0.82) for λL and λS respectively. Finally, the mediolateral direction tends to exhibit lower standard error of the mean and standard difference of the deviations
Reynard et al. 2014[37]	Local dynamic stability (LDS) can differentiate between healthy and non-healthy walkers, and potential correlation between LDS and cadence. LDS over one step is more reliable than one stride (ICC, 0.86 vs 0.82; SEM, 20% vs 27%). Larger variability was observed in the patient group, as was a slower cadence (-13%; CV 11%) compared to controls (CV 6%). Mediolateral gait stability was reduced by 33% in the patient group compared to the control group. There also appears to be a positive association

	between cadence and LDS in healthy controls that may be lacking in the patient group. The reliability of LDS seems sufficient to assess small differences between groups however longer walking tests are required to assess changes on an individual level.
Riva et al. 2014	Harmonic ratio decreased along anteroposterior and vertical directions with directional change. None of the other measures were affected by sampling frequency or directional change.
Russel & Haworth 2014[21]	The coefficient of variation (CV) for stride frequency did not differ between conditions, however peak knee flexion CV was significantly influenced by change in frequency. LDS was most stable at the preferred stride frequency of walking and decreased with faster and slower frequencies.
Segal et al. 2008[30]	Hip, right knee, and ankle maximum Lyapunov exponent values all varied significantly from straight line walking to turning, indicating increased instability at these locations while turning. Down-sampling by 1%,5% and 10% had no effect on outcome measures. The results demonstrate higher rates of kinematic separation during turning compared to straight-line walking, for the hip, right knee, and ankle joint trajectories, suggestive of decreased LDS for turning.
Son et al. 2009[57]	No statistically different differences between males and females for left hip and right knee. Significant differences were found in LyE values of the ankle. The results of this study were intended to act as normative values.
Terrier et al. 2013[11]	Most patients exhibited higher stability (i.e. lower maximum Lyapunov value) with orthopaedic shoes (19 for mediolateral (ML), 18 for vertical (V), and 17 for anteroposterior (AP). LDS was significantly improved by orthopaedic shoes along three axes, ranging from 7%AP; 10%ML. Step frequency did no differ between conditions. Significant reductions in visual analogue scale scores were evident with the orthopaedic shoes decreasing (29%). Most substantial improvement in LDS was along the ML direction. Foot orthotics had a significant effect of reducing pain and increasing LDS. Future studies should work towards making LDS a practical diagnostic tool.
Terrier & Reynard 2015[31]	No significant effect of age was found for anthropometrics or spatiotemporal characteristics. Dynamic stability measures were equal among age categories for AP and V, LDS in the ML direction was significantly different between groups, 15% of the variance in ML was due to age. Future longitudinal studies following individuals over many years should be conducted to confirm whether LDS is a valid method for early identification of falling.
van Schooten et al. 2013[16]	No significant differences were found in LDS between sessions and trials. Mean short-term LyE values ranged from 0.64 to 1.55. Within sessions ICCs ranged from 0.74 to 0.92, between sessions ICC ranged from 0.38 to 0.63. The standard deviation of the distance (SDD) of the mean LyE was 8% to 46%. Best SDD were obtained for the full 9D state space (12% within; 20% between) and method 3) (9.5% within; 20% between). The within session reliability of short term LyE are good (ICC >0.7) However between session reliability is lower, indicating that LDS is dependent on the state space reconstruction, but is reliable enough for between group differences. On an individual level, only substantial changes may be indicative of meaningful effects on LDS as the SDD range was between 17-46%. To overcome this problem, an average over multiple days of testing would be required. Fixed delays and embedding dimensions for state space reconstruction yielded the best within- and between session test-retest reliability, as well as smallest SDD

Wu et al. 2015[47]	Backwards walking (BW) had a significantly slower walking speed (0.476 (0.048) m/s) compared to forward walking (FW) (0.72 ± 0.14 m/s); Vertical acceleration in BW showed significantly higher values (1.77 ± 0.07) vs (1.55 ± 0.07 for neck; (1.75 ± 0.06) vs (1.52 ± 0.07) for torso; 1.92 ± 0.04 vs 1.72 ± 0.08 for pelvis; for BW and FW respectively. Torso also showed significant difference in anteroposterior (AP) 2.44 ± 0.07 vs 2.19 ± 0.13 BW and FW respectively. Hip and knee rotation LDS values also differed sig from BW to FW; Hip 1.90 ± 0.05 vs 1.69 ± 0.12; knee 1.87 ± 0.07 vs 1.64 ± 0.08 BW and FW respectively. Finally, AB/AD differed significantly for knee and ankle; knee, 1.94 ± 0.07 vs 1.69 ± 0.09; and ankle 2.01 ± 0.09 vs 1.75 ± 0.13. Significantly poorer stability of the trunk in the vertical direction was found for BW compared to FW. Further investigations into the validation of the results OG and during daily life.
Beauchet et al. 2009[48]	No significant differences were found between participant trials. Stride velocity decreased significantly from 88 to 39%. 121.4 ±15.4 to 53.2 ± 21.6 cm/s. Decreased stride velocity accounted for increase in mean standard deviation (SD) and coefficient of variation (COV); SD 30.9 ± 12.0 m/s to 129.0 ± 151.6 m/s; COV 2.7 ± 1.0 % to 5.0 ± 2.8 %. Estimated trial reliability amounted to 96.3% for mean, 89.9% for CV and 93.1% for SD. Stride time variability increased while walking speed decreased even when considering adjustment for the participant's effect, repetition of trials and right, left asymmetry.
Hausdorff et al. 2001[25]	Long-range scaling exponents of $\alpha = 0.76 \pm 0.11$ were found for the original stride interval time series, whereas an $\alpha = 0.5 \pm 0.03$ after random shuffling. These both indicate the presence of long-range fluctuations. Furthermore, long-range correlations at all three walking rates were present. Stride interval correlations depend on some aspect of the neuro-muscular control system that is not directly related to walking velocity or gait unsteadiness.
Kang & Dingwell 2006[38]	All divergence curves parameters were significantly greater during walking. None of the correlations between walking and standing mean divergence parameters were statistically significant, therefore LDS of standing did not predict that of walking. Measurement noise may have affected velocity calculations, this could have influenced short-term divergence behaviour. Additionally, walking on a treadmill incurred a constant walking speed, and may have artificially enhanced walking LDS
Kang & Dingwell 2009[19]	Peak EMG amplitude increased with speed for all muscles measured. Older adults (OA) displayed greater amplitudes in vastus lateralis, biceps femoris and gastrocnemius. Both λS and λL increased with speed, furthermore, higher values were observed for elderly subjects. Fmax for older adults was larger but did not have a significant interaction with speed. OA showed greater inter-stride variability of muscle activation patterns during gait, however EMG fail to account for muscle activation dynamics over multiple consecutive strides or synergy. LDS of multivariate dynamics and EMD were strongly correlated even when age and speed were accounted for. Future research should investigate the role of neural noise in the brain and motor function of older adults.

Kurz & Stergiou 2007[58]	The simulation results showed increased Lyapunov values with increased toe-off impulse (e.g. if the toe-off was used to assist forward progression of the centre of mass). The model, therefore, predicts that an increase in propulsive forces that govern forward translation of the centre of mass during stance phase will result in a linear increase in the magnitude of the largest Lyapunov exponent. Experimental results indicate that the nonlinear structure of the ankle and hip joints movement patterns altered as horizontal assistance was increased. Horizontal propulsive forces that are applied during the stance phase influence the nonlinear structure of human locomotion. The experimental results infer that changes in the nonlinear structure may be related to the proper utilization of the hip and ankle joint musculature to control the forward progression of the COM
Nessler et al. 2009[50]	Significant differences were found for λL (4-10) exponents between solo and forced condition, no significant difference was found for the λS condition
Bizovaka et al.2017[22]	Significant differences were found between fallers and non-fallers in Tinetti balance assessment tool (TBAT) scores, Shannon entropy (ShE) of the anteroposterior trunk (AP), ShE of the mediolateral shank (ML). Significant differences were found only for the ShE, sample entropies and the index of complexity were not able to distinguish between groups. Highly functioning elderly fallers could not be identified by variables derived from multiscale entropy approach. Further investigation into the applicability of the Shannon Entropy method is required.
Stout et al. 2016[32]	Detrended fluctuation analysis revealed no significant effect of using a safety harness while walking on a treadmill. Additionally, no significant effect was observed for age group indicating that the findings hold for both young and elderly age groups.
Reynard & Terrier 2015[33]	Participants walked at a lower speed while blindfolded (decrease of -00.19m/s) compared to the eyes open condition. Walking with eyes closed reduced step length and cadence resulting in a significantly lower walk ratio from 0.31 ± 0.04 to 0.28 ± 0.05 m/s. This was further decreased from the preferred walking speed with eyes closed (PWSEC) 0.30 ± 0.06 m/s. Participants did not exhibit any significant changes in trunk acceleration variability. Interestingly, PWSEC brought about higher divergence components for short-term stability but lower divergence components for long-term stability. Therefore, the changes were speed driven as opposed to deprivation driven.
Wu et al. 2007[26]	Kernel based principal component analysis can extract the nonlinear features of walking, distinguishing between young adults and elderly. Future research should aim to use the KCPA technique to analysis a variety of gait parameters, working towards making the techniques clinically applicable.
Dingwell & Marin 2006[49]	Kinematic output variability increased significantly with increased perturbation, as did λS. However, λL did not change. No significant differences were seen in orbital stability. Since the model's global basin remained consistent throughout all simulations, the amplitude of the perturbations was directly related to the model's risk of falling. Despite considerable local instability (λS and Mean standard deviation), global and orbital stability remained intact. Further development of models that more closely replicate human walking.

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