Human Movement Science 71 (2020) 102615

Contents lists available at ScienceDirect

Human Movement Science

journal homepage: www.elsevier.com/locate/humov

Full Length Article

Physical and perceptual measures of walking surface complexity strongly predict gait and gaze behaviour

Nicholas D.A. Thomas[a,b,*], James D. Gardiner[b], Robin H. Crompton[b], Rebecca Lawson[a]

[a] Institute of Population Health Sciences, University of Liverpool, Liverpool L69 7ZA, United Kingdom
[b] Institute of Ageing & Chronic Disease, University of Liverpool, Liverpool L7 8TX, United Kingdom

ARTICLE INFO

Keywords:
Stability
Surface complexity
Gait
Measures

ABSTRACT

Background: Walking surfaces vary in complexity and are known to affect stability and fall risk whilst walking. However, existing studies define surfaces through descriptions only.
Objective: This study used a multimethod approach to measure surface complexity in order to try to characterise surfaces with respect to locomotor stability.
Methods: We assessed how physical measurements of walking surface complexity compared to participant's perceptual ratings of the effect of complexity on stability. Physical measurements included local slope measures from the surfaces themselves and shape complexity measured using generated surface models. Perceptual measurements assessed participants' perceived stability and surface roughness using Likert scales. We then determined whether these measurements were indicative of changes to stability as assessed by behavioural changes including eye angle, head pitch angle, muscle coactivation, walking speed and walking smoothness.
Results: Physical and perceptual measures were highly correlated, with more complex surfaces being perceived as more challenging to stability. Furthermore, complex surfaces, as defined from both these measurements, were associated with lowered head pitch, increased muscle coactivation and reduced walking smoothness.
Significance: Our findings show that walking surfaces defined as complex, based on physical measurements, are perceived as more challenging to our stability. Furthermore, certain behavioural measures relate better to these perceptual and physical measures than others. Crucially, for the first time this study defined walking surfaces objectively rather than just based on subjective descriptions. This approach could enable future researchers to compare results across walking surface studies. Moreover, perceptual measurements, which can be collected easily and efficiently, could be used as a proxy for estimating behavioural responses to different surfaces. This could be particularly valuable when determining risk of instability when walking for individuals with compromised stability.

1. Introduction

Walking surfaces are hugely diverse, differing in size, materials and environmental setting. Together these factors influence how we walk, with some surfaces being more challenging to maintain stability than others. Self-reported questionnaires have shown that

* Corresponding author at: Institute of Population Health Sciences, University of Liverpool, Liverpool L69 7ZA, United Kingdom.
E-mail address: N.Thomas3@liverpool.ac.uk (N.D.A. Thomas).

https://doi.org/10.1016/j.humov.2020.102615
Received 28 August 2019; Received in revised form 13 March 2020; Accepted 19 March 2020
Available online 28 March 2020
0167-9457/

more complex surfaces cause an increase in falls when walking (Chippendale & Boltz, 2015; Nyman, Ballinger, Phillips, & Newton, 2013; Talbot, Musiol, Witham, & Metter, 2005). One common method to determine fall risk, including when walking over complex surfaces, is from assessing stability. However, there is currently no universally accepted measure for stability; rather, a variety of stability metrics have been proposed (as reviewed in Bruijn, Meijer, Beek, & Van Dieën, 2013), each with their own advantages and limitations.

To assess stability whilst walking over different surfaces, we first need to clarify what constitutes a complex surface. Here we take complexity to include uneven surfaces, slope changes and inconsistently spaced foot targets (Cham & Redfern, 2002; Graci, Elliott, & Buckley, 2010; Marigold & Patla, 2007; Matthis & Fajen, 2014; Merryweather, Yoo, & Bloswick, 2011; Patla & Vickers, 2003; Thies, Richardson, & Ashton-Miller, 2005) but not slippery or compliant surfaces or obstacles (Cham & Redfern, 2002; Graci et al., 2010; Morgan, Hafner, & Kelly, 2017). Stairs are also challenging to our stability (Bosse et al., 2012; Wang et al., 2017) though they are rarely classified as complex surfaces.

Although previous research has described a broad range of surfaces as complex, few studies have tried to objectively quantify surface complexity by measuring physical characteristics such as mechanical properties and micro and macro structure (e.g. topography, shape, size and location). Physical complexity of surfaces has previously been assessed through the international roughness index (Sayers, 1984), however this measurement is mostly used for roads and also requires vehicle characteristics. Assessment of surfaces has been attempted using the sidewalk condition index (Corazza, Di Mascio, & Moretti, 2016), but this method focuses exclusively on pedestrianised surfaces and the number of surface distresses (potholes, deformation from roots, etc.). Other studies that have analysed physical differences between surfaces have only assessed tactile perception using handheld materials (Skedung et al., 2011; Tiest & Kappers, 2006). There is as yet no widely accepted, objective means of measuring the physical characteristics of surfaces relevant to predicting walking stability.

In addition to quantifying walking surfaces complexity we also needed to assess people's stability whilst walking over each surface. Complex surfaces are likely to cause behavioural changes indicative of the person's stability, since it may reasonably be assumed that complex surfaces increase fall risk. Whilst no single measure of stability has been universally accepted, several behavioural measures might provide a proxy for stability. For example, people lower their gaze to look closer to their feet when they walk over complex surfaces, and they increase the number of fixations to the walking surface (Marigold & Patla, 2007; Matthis, Yates, & Hayhoe, 2018; 't Hart & Einhauser, 2012; Thomas, Gardiner, Crompton, & Lawson, 2020a). Similarly complex surfaces cause people to shorten their step length, lower their walking speed, increase leg muscle coactivation and walk more asymmetrically (Dixon et al., 2018; Marigold & Patla, 2008; Menant, Steele, Menz, Munro, & Lord, 2009; Voloshina, Kuo, Daley, & Ferris, 2013). Such behavioural measures could help us to understand stability but they are often time-consuming and difficult to record. Finding alternative metrics of stability that are easier to assess could be useful.

One potential measure of the effect of complexity on stability could be from assessing people's perception. No research, to the authors' knowledge, has assessed whether people's perception of their stability on complex surfaces is accurate. However, research assessing the perception of walking up stairs has shown that people can accurately identify when stairs are too high for safe walking (Konczak, Meeuwsen, & Cress, 1992; Warren Jr., 1984). The use of perceptual ratings to assess stability over complex surfaces may be more effective than focussing on separate physical measures given that people find it easier to categorise by combining multiple aspects, rather than a single dimensions (Ramscar & Hahn, 2001). For example, people may readily be able to take into account surface gradient, regularity and slipperiness when assessing perceived stability. If perceptual measures provide a sensitive measure of physical surface complexity, and if they also predict behavioural measures of stability, then it would be far easier, quicker and cheaper to use perceptual measures in future research rather than assessing complexity or stability.

In summary, surface complexity is known to influence stability whilst walking but few studies measure objective properties of the walking surfaces, with most relying on qualitative and subjective descriptions (e.g. rough vs smooth). Here, we attempt to rigorously quantify the complexity of walking surfaces using a variety of both physical and perceptual metrics to try to categorise surfaces with respect to walking stability. We assessed how surface complexity, specified using physical measures, may alter walking stability as reflected by changes in eye and head pitch angle, gait speed, harmonic ratios and muscle co-activation. These behavioural measures have all been previously assessed in relation to walking stability. We also investigated how physical measures of surface complexity correlated to perceptual measures of the effect of complexity on stability, in the hope of providing a quick and easy alternative to these behavioural measures. We aim to develop a simple, meaningful and convenient measure for the effect of surface complexity on stability whilst walking over surfaces of different complexity.

2. Methodology

The University of Liverpool's Ethics Committee granted ethical approval for the study in November 2017 (REF: 2672). We discuss the methodology for the physical, perceptual and behavioural measurements in separate sections. We assessed 17 surfaces for all three classes of measurements. As surfaces are multidimensional, we selected a wide range of typical urban surfaces in the study and included multiple examples of each broad class to allow an assessment of generalisability. The 17 surfaces were all located on the University of Liverpool campus, see Fig. 1, and Table 1. Surfaces are numbered in the order they were encountered for the perception and behaviour measurement tasks for half of the participants, the remaining participants encountering the surfaces in the reverse order. The surfaces were at least 10 m long to ensure that participants walked far enough to achieve a steady state of walking (Najafi, Miller, Jarrett, & Wrobel, 2010).

Fig. 1. Images showing the 17 surfaces used in the study. Two images (S17A & S17B) are shown for surface 17 as it included both a corridor section and stairs.

2.1. Physical measurements

2.1.1. Creating 3D models of the surface structure

In order to compare physical measures of surface complexity, we created 3D models using photogrammetry. This technique creates models through a series of overlapping photographs of a surface taken from different angles. For each of the 17 surfaces, an area of 1m^2 (2 m along the direction of walking x 0.5 m perpendicular to that direction) was used to create the models. Two separate models were created for each of the three surfaces with two distinct parts (S5, S14, S17). At least 35 pictures were taken to create each model, with photographs covering the maximum possible angle range of the surface. A Nikon D7200, 24 megapixel, camera was used, with an image resolution of 4000 × 6000 pixels. The 3D models were created using AgiSoft PhotoScan Standard (Version 1.4.4) software. To create the models, we only used high quality images, as determined by the “Estimated image quality” function in the

Table 1
Descriptions and approximate surface lengths (to the nearest metre) for the 17 surfaces. Three surfaces were split into two parts, listed as part A and B.

Surface label	Description of the surface	Approximate length (metres)
S1	Flagstone paving	29
S2	Oblique paved slope	29
S3	11 outdoor concrete stairs including two landings	13
S4	Flagstone paving	31
S5(A & B)	Three concrete stairs (A) and flagstone paving (B)	28
S6	Loose stones	30
S7	Brick slope	35
S8	Brick paving	31
S9	Fine gravel	30
S10	Small, loose pebbles	19
S11	Rough grass	34
S12	13 concrete stairs including two landings	10
S13	13 concrete stairs including two landings	10
S14(A & B)	Fine gravel (A), and level grass (B)	35
S15	Stones set in concrete	31
S16	38 indoor, polished stairs including three landings	15
S17(A & B)	Indoor corridor (A) and 18 polished stairs including one landing (B)	29

software. Once created, we used Meshlab software (Cignoni et al., 2008) to simplify each model to 20,000 triangular faces.

2.1.2. 1st physical measure: relief index derived from the 3D models

From each of the 3D models we calculated the relief index as a proxy for the surface's complexity. The relief index is defined as the ratio between the 3D surface area of the 3D model and its 2D planar area. This technique has been used as a metric for teeth morphology (Boyer, 2008; M'kirera & Ungar, 2003), and has since been implemented for quantifying large land surface areas (Szypula, 2017). To the authors' knowledge, it has not previously been used as a metric for smaller surface areas.

As this technique has not been used before for localised surfaces like ours, we completed a pilot study to check the replicability of the relief index measure. We created models from two 1 m × 0.5 m surfaces not used in the main study, flat paving slabs and a cobbled road comprised of setts. Three models were produced for each of these surfaces, with the photographs for each model taken on different days (A, B and C). We then calculated the relief index for each model as detailed above. The relief indexes are shown in Table 2.

The three relief indexes for both surfaces were similar, see Table 2. Thus, the models created using this method did not appear sensitive to changes due to lighting or the angle of the photograph used to create them, with the difference in relief index between the paved and cobbled models substantially greater than the differences between the relief indices for each surface (around 0.024 versus 0.001).

The 17 surface models originally consisted of varying numbers of faces (from 30,000 to 260,000 faces). We calculated the percentage change in the relief index calculated using the simplified model with 20,000 faces that we report here compared to the relief index calculated using the model with the original number of faces. The mean (± standard deviation) percentage change in the relief index was just 0.27% (± 0.61%) so standardising face number to 20,000 had little influence on the relief index.

2.1.3. 2nd physical measure: Dirichlet Normal Energy (DNE) derived from the 3D models

The 3D models of the surfaces were also used to calculate the Dirichlet Normal Energy (DNE) which reflects the local curvatures across the 3D model surface (see Bunn et al., 2011). Like the relief index, the DNE can be used as a proxy for surface complexity. However, it differs from the relief index in that the calculation can be weighted towards reflecting either finer or broader changes rather than providing a single measure for the entire surface. This method has been used as a complexity metric for teeth (e.g. Pampush et al., 2016) and bone morphology (Gardiner, Behnsen, & Brassey, 2018; Wallace, Winchester, Su, Boyer, & Konow, 2017).

We used the method described by (Shan, Kovalsky, Winchester, Boyer, & Daubechies, 2019), to calculate DNE using their improved algorithm “ariaDNE”. We weighted the calculation towards reflecting localised changes that would be detectable by the feet when walking, relative to more general surface changes such as the level change between different stairs. For further details, see the supplementary material (SM1).

Table 2
The relief indexes calculated from the three photogrammetry 3D models of each of the surfaces.

	Set A model	Set B model	Set C model
Paved	1.012	1.012	1.011
Cobbled	1.036	1.036	1.037

2.1.4. 3rd physical measure: local slope angle

A final, simpler physical measure was used based on the local slope of each surface. This measure of slope angle did not require surface modelling, but rather used a clinometer to measure the mean local slope angle (°) of a flat, 12 cm long extent placed onto the surface. This was done at 20 locations along each surface, with each location separated by approximately 30 cm.

2.2. Perception measurements

2.2.1. Participants

Only participants that had no impairments or injuries that might affect their gait or vision were tested. The study consisted of 32 participants, 14 male, mean ± SD; age = 22.2 ± 5.0 years; height = 172.6 ± 8.5 cm. Twelve of these participants (10 male, age = 27.3 ± 4.3 years; height = 178.0 ± 6.9 cm) had already completed the behavioural part of the study, but there were no significant differences between their mean responses across the three different ratings and those of the remaining 20 participants, ($F(1, 32) = 0.22$, $\eta_p^2 = 0.01$, $p = .643$) so responses were pooled in the analyses reported here.

2.2.2. Data collection, protocol & analysis

Participants rated their perception of the 17 different surfaces using a Likert scale between 1 and 10 (Likert, 1932). For surfaces with two components (i.e. S5, S14 & S17), participants were asked to consider both parts and to provide an overall rating. Participants rated each surface from vision alone for, first, surface roughness (1 = "completely smooth" to 10 = "extremely rough") and second, stability (1 = "no problem with stability" to 10 = "I think I might fall over") if they were to walk on the surface. They then walked over the surface, and re-rated stability after having walked on it. Finally they described each surface in a maximum of three words.

2.3. Behavioural measurements

2.3.1. Participants

Twenty healthy adults (14 male, age = 26.6 ± 4.2 years; height = 176.1 ± 9.1 cm) were recruited for the study. All participants had no impairments or injuries that might affect their gait or vision.

2.3.2. Data collection

We used multiple gaze and gait measures to provide converging evidence about stability because, as discussed in the introduction, there is no single, agreed measure of stability during locomotion. Eye movements were recorded using a Pupil Labs eye-tracking headset (Kassner, Patera, & Bulling, 2014) that recorded pupil movement at 30 Hz and a world view at 60 Hz. We were interested in how the stability of walking on surfaces influenced vertical gaze so we only analysed pupil movement in the vertical direction. Six Delsys TRIGNO™ sensors (IMUs, Boston, MA, USA) were placed on the participant. Four of these sensors were used to collect inertia data, recorded at 148 Hz. A sensor on the forehead collected gyroscopic data which was used to calculate head pitch. Another sensor was positioned on the lower lumbar region. This provided accelerometery data that was used to calculate harmonic ratios to measure gait symmetry, following Bellanca, Lowry, VanSwearingen, Brach, and Redfern (2013). Two sensors were positioned above the malleoli on each legs which were used to calculate gait events. The remaining two sensors were used to collect surface electromyography (sEMG) data, recorded at 1111 Hz. These sensors were positioned on the antagonistic muscles of the right lower limb, the *Tibialis Anterior* muscle and the medial head of the *Gastrocnemius* muscle.

The eye-tracker was calibrated then participants walked at a self-selected speed over the 17 surfaces (see Fig. 1 and Table 1), from S1 to S17 for half of the participants and in the reverse order (from S17 to S1) for the remaining participants. We also collected data that we report in a companion paper (Thomas, Gardiner, Crompton, & Lawson, 2020b) when people walked over the same 17 surfaces but with their lower vision blocked. The order of this factor (full versus partial vision) was counterbalanced across participants. There was no significant difference for any of the measures depending on the different orders of completion of the study, $F(1, 18) = 0.38$, $\eta_p^2 = 0.02$, $p = .544$. Participants stood still in front of each surface for three seconds before walking at a self-selected speed to the end of the surface and then stood still for a further three seconds.

2.3.3. Analysis

Mean eye and head pitch angles were calculated for each participant for each surface. During calibration of the eye tracker, participants fixated a target set at the participant's own eye height and this angle was used to define an eye angle of 0°. All vertical eye movements were converted into angular deviations from 0°, with lower gaze, towards the feet, producing more negative eye angles. A head pitch angle of 0° was defined as the average head position at the static period at the start and end of each surface trial, following Thomas et al. (2020a). Head pitch angles were calculated using the gyroscopic data from the forehead sensor. The gyroscopic data were filtered using a low pass, 10 Hz fourth-order Butterworth filter to reduce noise. Similar to Takeda et al. (2014), signal drift was then removed using the period when the participant remained still at the start and end of each trial to provide a baseline. The gyroscopic data (rotational velocity in deg./s) were numerically integrated for each surface to give head pitch angle.

Mean gait speed was calculated from the approximate length of the surfaces (see Table 1) and from gait events timings, calculated from gyroscopic data at the ankles (Li, Young, Naing, & Donelan, 2010).[1]

Mean harmonic ratios were calculated from anteroposterior accelerometery data from the lumbar IMU. Harmonic ratios were calculated by taking a Fourier transform of the data for each stride. The harmonic ratio is the ratio between the sum of the amplitudes of the even harmonics (representative of symmetrical gait) and the sum of the amplitudes of the odd harmonics (representative of asymmetrical gait) (Gage, 1964; Smidt, Arora, & Johnston, 1971). A higher ratio represents more symmetrical, smoother gait. We only considered harmonic ratios in the anteroposterior direction since this direction has previously been found to show the greatest changes when walking (Brach et al., 2010; Lowry, VanSwearingen, Perera, Studenski, & Brach, 2013).

Surface EMG signals were calculated between adjacent ipsilateral gait events. Muscle co-activation was then calculated following Winter (2005) defined by the following equation:

$$\%COCON = 2 \times \frac{common\ area\ A\&B}{area\ A + area\ B} \times 100\%$$

where %COCAN is the percentage of muscle coactivation between the two muscles, area A is the area below the EMG curve of muscle A (*Tibialis Anterior)*, area B is the area below the EMG curve of muscle B (medial head of the *Gastrocnemius*) and the common area A & B is the common area between both muscles.

For eye angle, head pitch angle, harmonic ratios and muscle coactivation, the first two and last two strides for each surface were removed from the mean calculation to avoid the influence of starting and stopping walking1. *Z*-scores of means were then calculated using the mean and standard deviation value from each measure. The z-scores for the physical, perceptual and muscle co-activation measures were multiplied by -1 so that, for all measures, higher z-scores were always associated with more stable walking or less complex surfaces.

For the results, we focused on correlations between different measures. This was due to our large range of measures in addition to the range of walking surfaces, allowing us to investigate the relation between these factors depending on surface characteristics. Large correlations (abs(r) $>$ 0.5) as determined by Cohen (2013), are highlighted in each correlation table. To reduce the risk of making Type 1 errors all statistical tests reported used an alpha level of 0.05 that was then adjusted for each correlation table using the Bonferroni correction, based on the number of correlations executed. These calculated *p*-values are reported with each table.

3. Results

The results are split into two sections. Firstly we assessed how the three physical measures of surface complexity related to the three perceptual measures on the effects of complexity on stability. Secondly we assessed how these six measures correlated to the five behavioural measures of stability. Mean values for all measures are provided in the supplementary material (SM2).

3.1. Assessing the relation between physical and perceptual measures of surface complexity

Pearson's correlations were calculated across the mean z-scores for the 17 surfaces between all three physical and all three perceptual measures, see Table 3.

Correlations were generally low for the relief index (the ratio of the surface to planar area). We realised that this could have been caused by the high relief indexes occurring for surfaces with stairs. Since we do not normally step on the vertical surfaces of stairs this may have produced a misleading ratio. We therefore repeated the Pearson's correlations between relief index and the other measures for only the 11 surfaces without stairs, see Table 4.

Removal of the six surfaces containing stairs increased correlations for the relief index, as well as for most other measures. The largest correlation values were found within the three physical measures and within the three perceptual measures, all of which were significant.

To investigate further the relationship between physical and perceptual measures we conducted a principal components analysis (PCA). Two components were established based on a criteria of the component accounting for at least 10% of the variance, see Fig. 2.

The shared surface features within groups of surfaces may explain why they generally cluster together. The two most common verbal descriptions given by participants to each group of surfaces represented by the different colours were smooth and paving for the red circles, stairs and steps for the blue squares and pebbles and uneven for the orange triangles. For further details please see the supplementary material (SM3). These three groups of surfaces will henceforth be described as smooth (red circles), stairs (blue circles) and uneven (orange triangles).

3.2. Assessing the relation between behavioural measures and physical and perceptual measures

For this section we excluded the three surfaces that had two distinct components (S5, S14 and S17). These surfaces caused technical challenges when calculating behavioural means and behaviour may differ in anticipation of the transition from one component to the other. For further details see the supplementary material (SM4).

Pearson's correlations were calculated across the mean z-scores for the remaining 14 surfaces between all five behavioural measures, see Table 5. We compared these correlations to those obtained by calculating within-participant correlations for the 12

[1] We had intended speed to be calculated from gait events and accelerometric data recorded from IMUs on the legs, however the accelerometric data did not record properly due to a fault with these IMUs. The gyroscopic data used to calculate gait events was not affected. Thus a simpler measure was used to calculate gait speed, namely taking the time between the two stationary periods at the start and end of each trial, and dividing this by the approximate length of the surface.

Table 3
Correlations between the mean z-scores for all 17 surfaces for every pair of physical and perceptual measures.

	DNE	Relief index	Roughness rating	Pre-walk stability rating	Post-walk stability rating
Mean local slope angle	**0.89***	0.13	**0.78***	**0.63***	**0.72***
DNE	-	**0.50**	**0.67***	**0.54**	**0.63***
Relief index	-	-	0.15	0.14	0.15
Roughness rating	-	-	-	**0.94***	**0.94***
Pre-walk stability rating	-	-	-	-	**0.98***

Shaded correlation values are between physical and perceptual measures. Bold values represent large effect sizes (abs(r) > 0.5) as determined by Cohen (*2013*)
* signifies p < .003 (calculated using the Bonferroni adjustment).

Table 4
Correlations between the mean z-scores for the 11 surfaces (excluding the six surfaces with stairs) for every pair of physical and perceptual measures.

	DNE	Relief index	Roughness rating	Pre-walk stability rating	Post-walk stability rating
Mean local slope angle	**0.95***	**0.92***	**0.79***	**0.63**	**0.71***
DNE	-	**0.98***	**0.69**	**0.55**	**0.65**
Relief index	-	-	**0.68**	**0.55**	**0.66**
Roughness rating	-	-	-	**0.95***	**0.96***
Pre-walk stability rating	-	-	-	-	**0.99***

Shaded correlation values are between physical and perceptual measures. Bold values represent large effect sizes (abs(r) > 0.5), as determined by Cohen (2013). * signifies p < .003 (calculated using the Bonferroni adjustment).

participants that completed both the behaviour and perception task. Correlations were lower, but showed a similar pattern, see the supplementary material (SM5).

Next we analysed how perceptual and physical measures compared to behavioural measures indicative of stability. Pearson's correlations were calculated across the mean z-scores between all five of the behavioural measures and all six of the physical and perceptual measures, see Table 6. As surfaces containing stairs were shown to reduce perceptual and physical correlations, we also

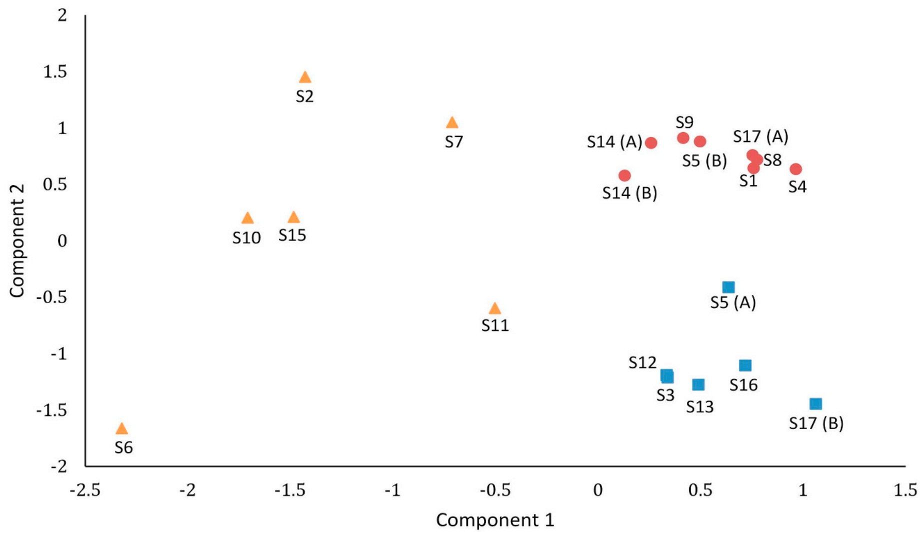

Fig. 2. A plot of the first two components of the PCA including the three physical and three perceptual measures. Component 1 (variance = 66.4%) consisted of the roughness rating, pre-walk stability rating, post-walk stability rating, mean local slope angle and DNE. Component 2 (variance = 21.3%) consisted of DNE and the relief index. Two distinct groups were established based on their values; positive for both components (red circles, $n = 8$) and positive for component 1 only (blue squares, $n = 6$). The remaining surfaces (orange triangles) were less well grouped together but did all score negatively for component 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Correlations between the mean z-scores for the 14 surfaces (excluding the three surfaces with two components) for every pair of the five behavioural measures.

	Head angle	Gait speed	Harmonic ratios	Muscle coactivation
Eye angle	0.43	0.23	0.46	**0.60**
Head angle	–	**0.62**	**0.85***	**0.80***
Gait speed	–	–	**0.78***	**0.57**
Harmonic ratios	–	–	–	**0.68**

Bold values represent large effect sizes (abs(r) > 0.5), as determined by Cohen (2013).
* Signifies $p < .005$ (calculated using the Bonferroni adjustment).

Table 6
Correlations between the mean z-scores for 14 surfaces (excluding the three surfaces with two components) for the six physical and perceptual measures and the five behavioural measures.

	Eye Angle	Head Angle	Gait speed	Harmonic ratios	Muscle coactivation
Mean absolute slope angle	0.37	0.39	0.14	0.33	0.32
DNE	0.04	**0.52**	0.12	**0.52**	0.45
Relief index	0.16	**0.50**	**0.81***	**0.76***	0.49
Roughness rating	0.33	**0.71**	0.15	**0.61**	0.48
Pre-walk stability rating	0.49	**0.82***	0.28	**0.69**	**0.62**
Post-walk Stability rating	0.44	**0.82***	0.23	**0.65**	**0.63**

Bold values represent large effect sizes (abs(r) > 0.5), as determined by Cohen (2013).
* Signifies $p < .0017$ (calculated using the Bonferroni adjustment).

analysed surfaces when excluding stairs, see Table 7. Perceptual measures produced better estimates of behavioural stability measures than physical measures. Head angle and harmonic ratios were particularly strongly correlated. In contrast, eye angle did not correlate significantly with any measure.

We conducted a further PCA to investigate the relationship between the physical, perceptual and behavioural measures. Three components were established based on the same criteria as the previous PCA, see Fig. 3.

To determine an overall stability score for each individual surface, we calculated mean z-scores for each of the 14 single part surfaces across all the 11 measures (3 physical, 3 perceptual and 5 behavioural). These mean z-scores are shown ranked from smallest to largest in Fig. 4.

Table 7
Correlations between the mean z-scores for 10 surfaces (excluding both stairs and surfaces with two components) for the six physical and perceptual measures and the five behavioural measures.

	Eye Angle	Head Angle	Gait speed	Harmonic ratios	Muscle coactivation
Mean absolute slope angle	0.15	**0.60**	**0.54**	**0.73**	**0.63**
DNE	0.10	**0.61**	0.48	**0.68**	**0.66**
Relief index	0.11	**0.64**	**0.55**	**0.68**	**0.68**
Roughness rating	0.48	**0.89***	**0.80**	**0.92***	**0.81***
Pre-walk stability rating	**0.68**	**0.93***	**0.86***	**0.93***	**0.86***
Post-walk stability rating	**0.63**	**0.95***	**0.88***	**0.94***	**0.90***

Bold values represent large effect sizes (abs(r) $>$ 0.5), as determined by Cohen (2013).
* Signifies $p < .0017$ (calculated using the Bonferroni adjustment).

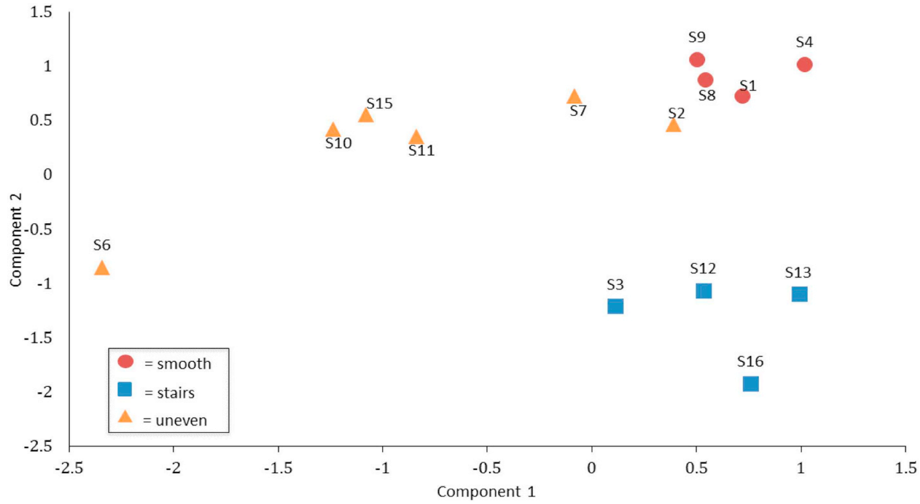

Fig. 3. A plot of the first two components of a Principal Component Analysis (PCA) between the 5 behavioural, 3 perceptual and 3 physical measurements. Surfaces are coloured based on the three groups established in Fig. 2. Component 1 (variance = 55.3%) consisted of mean local slope angle, DNE, roughness rating, harmonic ratios, pre-walk stability rating, post-walk stability rating and head angle. Component 2 (variance = 20.6%) consisted of relief index, speed, harmonic ratios, head angle, muscle coactivation and DNE.

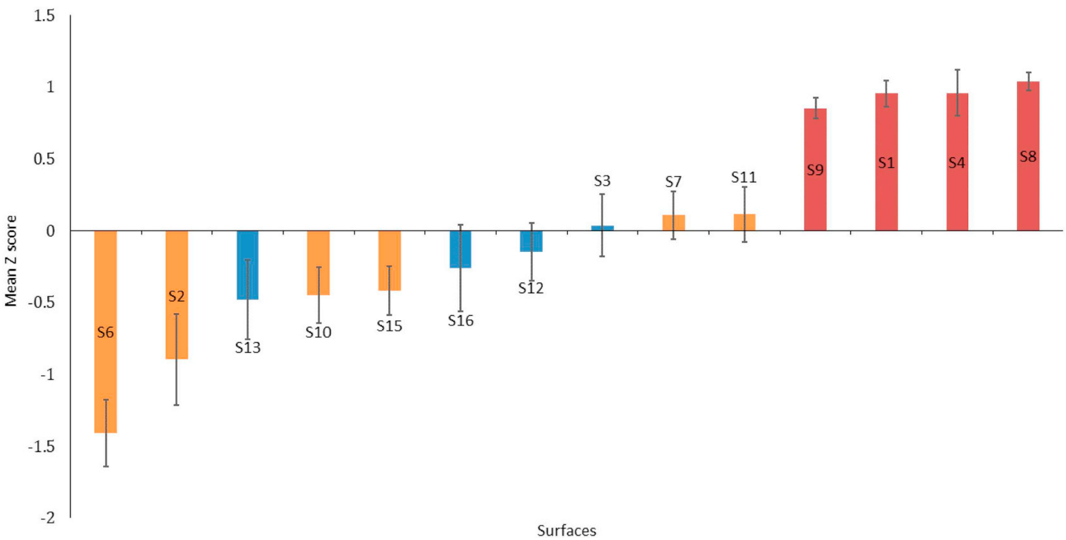

Fig. 4. Ranked mean (± SE) z-scores for each of the 14 single part surfaces across all the 11 measures. Lower z-scores are indicative of more difficult surfaces, i.e. more complex and less stable for walking over. Surfaces are coloured according to the same smooth (red), stairs (blue) and uneven (orange) groups used in Figs. 2 and 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

The aim of this study was twofold. Firstly we wanted to see whether more complex surfaces (as assessed from physical measurements) were perceived as more challenging to our stability, and secondly whether this perception translated to reductions in stability, as assessed from a range of behavioural measures. Complex surfaces were, indeed, perceived as more challenging, with increases in physical roughness being correlated with a perception of greater roughness and greater predicted unsteadiness when walking over them. Furthermore, perceptual and physical measures predicted a subset of our behavioural measures.

Comparisons between physical and perceptual measurements also established three general types of surfaces as shown in Fig. 2. These groups were labelled smooth, stairs and uneven based on common verbal descriptions of the surfaces that were provided as part of the perception study. Uneven surfaces were less well grouped and spanned a range of materials, topographies and perceptions of walking stability. In previous research, smooth and uneven or irregular surfaces were not objectively defined, but rather relied on subjective descriptors (Marigold & Patla, 2007; Menz, Lord, & Fitzpatrick, 2003; Merryweather et al., 2011; Storm, Buckley, & Mazza, 2016; Tamburini et al., 2018; Thies et al., 2005). We believe that this is the first time that different walking surfaces have been more thoroughly characterised through the use of objective, physical measures and perceptual ratings. This result strengthens the argument for the use of more consistent terminology for studies using “uneven” or “irregular” surfaces. Additional or more precise descriptions (i.e. sloped, rocky, irregularly spaced targets etc.) are essential to prevent misleading comparisons.

The multimethod approach used in this study may encourage future studies to compare surfaces of different complexity. By using a range of different measures of surface complexity, we have been able to provide converging evidence about how the physical characteristics of surfaces influence stability and how these characteristics can be readily perceived. This method can be used to predict behavioural responses reflecting instability due to surface structure. Importantly, this study showed that simple, perceptual measures can predict changes in behaviour as effectively as physical measures. This may provide researchers with an efficient and effective tool to anticipate the effect of complexity on stability before conducting behavioural studies on vulnerable populations. Researchers could use the method discussed here, determining surface characteristics from both physical and perceptual measures, before assessing behavioural changes. An improved understanding of surface complexity should allow future research to focus more precisely on behavioural changes due to stability fluctuating during locomotion.

This study found that perceptual and physical measures of surfaces are well correlated, as evidenced by generally large effect sizes, and, further, that both measures also correlate with a range of behavioural measures that have been proposed as proxy measures of stability during walking. All measures assessed smooth surfaces as providing high stability or as being less complex (see Fig. 4). How surface complexity impacted behaviour varied depending on the behaviour being assessed. Eye angle, in particular, was only weakly correlated with other behavioural measures (Tables 6 and 7) as well as with the perceptual and physical measures (Table 5). This is consistent with our recent finding that eye angle, unlike head pitch angle, remained relatively constant, fixed downward, regardless of the complexity of the surface type (Thomas et al., 2020a). As lowering of the eyes when walking is likely to require far less energy than lowering of the head, assessing more energetically costly behaviour may provide a better indicator of instability whilst walking. Indeed, our study showed muscle co-activation, walking smoothness assessed using harmonic ratios and head angle (all of which are likely to be more costly to vary than eye angle) all correlated more strongly with physical and perceptual measures than eye angle. An interesting opportunity for future research could be to determine how energetically costly different surfaces are for walking, and which components of locomotion contribute to this increase in energetic expenditure. Also, in this study we assessed average behaviour whilst walking over a given surface. Future research could compare changes in behavioural measures over much shorter time periods. This approach may show stronger associations between gaze and gait behaviour, similar to that reported recently by Matthis et al. (2018). Our next step will be to analyse how individual perceptual and behavioural measures vary in relation to surface complexity, and to compare the data collected in the present study to when participants' lower vision is blocked (Thomas et al., 2020b).

One common surface type that is often not considered complex, but which does impose challenges to our stability, is a flight of stairs. Stairs had a distinct effect on our perceived and behavioural measures of stability relative to irregular surfaces (Figs. 2 & 3). This may in part be due to stairs being uniform and so they permit repetitive, predictable gait. Indeed, walking on stairs does produce differences in gaze, muscle activation and in biomechanics when compared to flat level walking (Cromwell & Wellmon, 2001; McFadyen & Winter, 1988; Miyasike-DaSilva, Allard, & McIlroy, 2011; Shin & Yoo, 2016; Zietz & Hollands, 2009). These changes are associated with decreased stability and increased fall risk so stairs are important to consider. In this study, our behavioural measures suggested that people were relatively unstable when walking on stairs, and they also rated stairs as being relatively difficult to walk on. Due to the differences that we found for stairs compared to smooth and uneven surfaces, we conclude that stairs are best considered as their own distinct class of surface when analysing complexity.

5. Conclusions

In summary, we found that more complex surfaces (defined based on physical measurements) are perceived as more challenging to our stability during locomotion. Furthermore, perceptual and physical measures of surfaces predicted behavioural measures of stability, especially head angle, walking smoothness and muscle co-activation. Additionally, extra consideration should be taken when including surfaces with stairs into a study. We propose that perceptual measures may provide an easy and effective method to predict people's locomotor stability on different surfaces. This may be particularly useful for determining stability for those at greater risk of falls, where researchers may want to minimise directly testing walking but where it is important to test for individual differences in which surfaces may lead to instability.

Declarations of Competing Interest

None

Acknowledgments

This research was supported by a grant from the Economic Social Research Council, UK, to the first author [ES/J500094/1]. The authors wish to thank Rebecca McGrath for her assistance.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.humov.2020.102615.

References

Bellanca, J., Lowry, K., VanSwearingen, J., Brach, J., & Redfern, M. (2013). Harmonic ratios: A quantification of step to step symmetry. *Journal of Biomechanics, 46*, 828–831.

Bosse, I., Oberländer, K. D., Savelberg, H. H., Meijer, K., Brüggemann, G.-P., & Karamanidis, K. (2012). Dynamic stability control in younger and older adults during stair descent. *Human Movement Science, 31*, 1560–1570.

Boyer, D. M. (2008). Relief index of second mandibular molars is a correlate of diet among prosimian primates and other euarchontan mammals. *Journal of Human Evolution, 55*, 1118–1137.

Brach, J. S., McGurl, D., Wert, D., VanSwearingen, J. M., Perera, S., Cham, R., & Studenski, S. (2010). Validation of a measure of smoothness of walking. *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences, 66*, 136–141.

Bruijn, S., Meijer, O., Beek, P., & Van Dieën, J. (2013). Assessing the stability of human locomotion: A review of current measures. *Journal of the Royal Society Interface, 10*, 20120999.

Bunn, J. M., Boyer, D. M., Lipman, Y., St. Clair, E. M., Jernvall, J., & Daubechies, I. (2011). Comparing Dirichlet normal surface energy of tooth crowns, a new technique of molar shape quantification for dietary inference, with previous methods in isolation and in combination. *American Journal of Physical Anthropology, 145*, 247–261.

Cham, R., & Redfern, M. S. (2002). Changes in gait when anticipating slippery floors. *Gait & Posture, 15*, 159–171.

Chippendale, T., & Boltz, M. (2015). The neighborhood environment: Perceived fall risk, resources, and strategies for fall prevention. *Gerontologist, 55*, 575–583.

Cignoni, P., Callieri, M., Corsini, M., Dellepiane, M., Ganovelli, F., & Ranzuglia, G. (2008). Meshlab: An open-source mesh processing tool. *Eurographics Italian chapter conference*. *Vol. 2008*. *Eurographics Italian chapter conference* (pp. 129–136).

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences.* Routledge.

Corazza, M. V., Di Mascio, P., & Moretti, L. (2016). Managing sidewalk pavement maintenance: A case study to increase pedestrian safety. *Journal of Traffic and Transportation Engineering (English Edition), 3*, 203–214.

Cromwell, R., & Wellmon, R. (2001). Sagittal plane head stabilization during level walking and ambulation on stairs. *Physiotherapy Research International, 6*, 179–192.

Dixon, P. C., Schutte, K. H., Vanwanseele, B., Jacobs, J. V., Dennerlein, J. T., & Schiffman, J. M. (2018). Gait adaptations of older adults on an uneven brick surface can be predicted by age-related physiological changes in strength. *Gait & Posture, 61*, 257–262.

Gage, H. (1964). Accelerographic analysis of human gait. *ASME Paper* (pp. 64). .

Gardiner, J. D., Behnsen, J., & Brassey, C. A. (2018). Alpha shapes: Determining 3D shape complexity across morphologically diverse structures. *BMC Evolutionary Biology, 18*.

Graci, V., Elliott, D. B., & Buckley, J. G. (2010). Utility of peripheral visual cues in planning and controlling adaptive gait. *Optometry and Vision Science, 87*, 21–27.

Kassner, M., Patera, W., & Bulling, A. (2014). Pupil: An open source platform for pervasive eye tracking and mobile gaze-based interaction. *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing: Adjunct publication* (pp. 1151–1160). ACM.

Konczak, J., Meeuwsen, H. J., & Cress, M. E. (1992). Changing affordances in stair climbing: The perception of maximum climbability in young and older adults. *Journal of Experimental Psychology. Human Perception and Performance, 18*, 691–697.

Li, Q., Young, M., Naing, V., & Donelan, J. M. (2010). Walking speed estimation using a shank-mounted inertial measurement unit. *Journal of Biomechanics, 43*, 1640–1643.

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology, 140*, 1–55.

Lowry, K. A., VanSwearingen, J. M., Perera, S., Studenski, S. A., & Brach, J. S. (2013). Walking smoothness is associated with self-reported function after accounting for gait speed. *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences, 68*, 1286–1290.

Marigold, D. S., & Patla, A. E. (2007). Gaze fixation patterns for negotiating complex ground terrain. *Neuroscience, 144*, 302–313.

Marigold, D. S., & Patla, A. E. (2008). Age-related changes in gait for multi-surface terrain. *Gait & Posture, 27*, 689–696.

Matthis, J. S., & Fajen, B. R. (2014). Visual control of foot placement when walking over complex terrain. *Journal of Experimental Psychology-Human Perception and Performance, 40*, 106–115.

Matthis, J. S., Yates, J. L., & Hayhoe, M. M. (2018). Gaze and the control of foot placement when walking in natural terrain. *Current Biology, 28*(1224–1233), e1225.

McFadyen, B. J., & Winter, D. A. (1988). An integrated biomechanical analysis of normal stair ascent and descent. *Journal of Biomechanics, 21*, 733–744.

Menant, J. C., Steele, J. R., Menz, H. B., Munro, B. J., & Lord, S. R. (2009). Effects of walking surfaces and footwear on temporo-spatial gait parameters in young and older people. *Gait & Posture, 29*, 392–397.

Menz, H. B., Lord, S. R., & Fitzpatrick, R. C. (2003). Acceleration patterns of the head and pelvis when walking on level and irregular surfaces. *Gait & Posture, 18*, 35–46.

Merryweather, A., Yoo, B., & Bloswick, D. (2011). Gait characteristics associated with trip-induced falls on level and sloped irregular surfaces. *Minerals, 1*, 109–121.

Miyasike-DaSilva, V., Allard, F., & McIlroy, W. E. (2011). Where do we look when we walk on stairs? Gaze behaviour on stairs, transitions, and handrails. *Experimental Brain Research, 209*, 73–83.

M'kirera, F., & Ungar, P. S. (2003). Occlusal relief changes with molar wear in pan troglodytes troglodytes and Gorilla gorilla gorilla. *American Journal of Primatology: Official Journal of the American Society of Primatologists, 60*, 31–41.

Morgan, S. J., Hafner, B. J., & Kelly, V. E. (2017). Dual-task walking over a compliant foam surface: A comparison of people with transfemoral amputation and controls. *Gait & Posture, 58*, 41–45.

Najafi, B., Miller, D., Jarrett, B. D., & Wrobel, J. S. (2010). Does footwear type impact the number of steps required to reach gait steady state?: An innovative look at the impact of foot orthoses on gait initiation. *Gait & Posture, 32*, 29–33.

Nyman, S. R., Ballinger, C., Phillips, J. E., & Newton, R. (2013). Characteristics of outdoor falls among older people: A qualitative study. *BMC Geriatrics, 13*.

Pampush, J. D., Winchester, J. M., Morse, P. E., Vining, A. Q., Boyer, D. M., & Kay, R. F. (2016). Introducing molaR: A new R package for quantitative topographic analysis of teeth (and other topographic surfaces). *Journal of Mammalian Evolution, 23*, 397–412.

Patla, A. E., & Vickers, J. N. (2003). How far ahead do we look when required to step on specific locations in the travel path during locomotion? *Experimental Brain Research, 148*, 133–138.

Ramscar, M., & Hahn, U. (2001). *Similarity and categorization.* Oxford University Press.

Sayers, M. W. (1984). *Guidelines for the conduct and calibration of road roughness measurements*.

Shan, S., Kovalsky, S. Z., Winchester, J. M., Boyer, D. M., & Daubechies, I. (2019). Aria DNE: A robustly implemented algorithm for Dirichlet energy of the normal. *Methods in Ecology and Evolution*.

Shin, S. S., & Yoo, W. G. (2016). Comparison of trunk acceleration ratios during stair negotiation in old-old females. *Journal of Physical Therapy Science, 28*, 1922–1923.

Skedung, L., Danerlov, K., Olofsson, U., Johannesson, C. M., Aikala, M., Kettle, J., ... Rutland, M. W. (2011). Tactile perception: Finger friction, surface roughness and perceived coarseness. *Tribology International, 44*, 505–512.

Smidt, G. L., Arora, J. S., & Johnston, R. C. (1971). Accelerographic analysis of several types of walking. *American Journal of Physical Medicine & Rehabilitation, 50*, 285–300.

Storm, F. A., Buckley, C. J., & Mazza, C. (2016). Gait event detection in laboratory and real life settings: Accuracy of ankle and waist sensor based methods. *Gait & Posture, 50*, 42–46.

Szypula, B. (2017). Quantitative studies of the morphology of the South Poland using relief index (RI). *Open Geosciences, 9*, 509–524.

't Hart, B. M., & Einhauser, W. (2012). Mind the step: Complementary effects of an implicit task on eye and head movements in real-life gaze allocation. *Experimental Brain Research, 223*, 233–249.

Takeda, R., Lisco, G., Fujisawa, T., Gastaldi, L., Tohyama, H., & Tadano, S. (2014). Drift removal for improving the accuracy of gait parameters using wearable sensor systems. *Sensors, 14*, 23230–23247.

Talbot, L. A., Musiol, R. J., Witham, E. K., & Metter, E. J. (2005). Falls in young, middle-aged and older community dwelling adults: Perceived cause, environmental factors and injury. *Bmc Public Health, 5*.

Tamburini, P., Storm, F., Buckley, C., Bisi, M. C., Stagni, R., & Mazzà, C. (2018). Moving from laboratory to real life conditions: Influence on the assessment of variability and stability of gait. *Gait & Posture, 59*, 248–252.

Thies, S. B., Richardson, J. K., & Ashton-Miller, J. A. (2005). Effects of surface irregularity and lighting on step variability during gait: A study in healthy young and older women. *Gait & Posture, 22*, 26–31.

Thomas, N. D. A., Gardiner, J. D., Crompton, R. H., & Lawson, R. (2020a). *Look out: An exploratory study assessing how gaze (eye angle and head angle) and gait speed are influenced by surface irregularity.* (in press).

Thomas, N. D. A., Gardiner, J. D., Crompton, R. H., & Lawson, R. (2020b). *The importance of lower peripheral vision for gait stability.* (in preparation).

Tiest, W. M. B., & Kappers, A. M. L. (2006). Analysis of haptic perception of materials by multidimensional scaling and physical measurements of roughness and compressibility. *Acta Psychologica, 121*, 1–20.

Voloshina, A. S., Kuo, A. D., Daley, M. A., & Ferris, D. P. (2013). Biomechanics and energetics of walking on uneven terrain. *The Journal of Experimental Biology, 216*, 3963–3970.

Wallace, I. J., Winchester, J. M., Su, A., Boyer, D. M., & Konow, N. (2017). Physical activity alters limb bone structure but not entheseal morphology. *Journal of Human Evolution, 107*, 14–18.

Wang, K., Delbaere, K., Brodie, M. A., Lovell, N. H., Kark, L., Lord, S. R., & Redmond, S. J. (2017). Differences between gait on stairs and flat surfaces in relation to fall risk and future falls. *IEEE Journal of Biomedical and Health Informatics, 21*, 1479–1486.

Warren, W. H., Jr. (1984). Perceiving affordances: Visual guidance of stair climbing. *Journal of Experimental Psychology. Human Perception and Performance, 10*, 683–703.

Winter, D. A. (2005). *Biomechanics and motor control of human movement* (3rd ed.). Hoboken, New Jersey: John Wiley & Sons.

Zietz, D., & Hollands, M. (2009). Gaze behavior of young and older adults during stair walking. *Journal of Motor Behavior, 41*, 357–365.