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Investigating human locomotion outside of the laboratory

By
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Abstract

Understanding those factors most important to maintain stability when walking is critical in the prevention of age-related falls. As we age, intrinsic factors (traits affecting the individual) deteriorate and are associated with increased gait instability. Separately, extrinsic factors (environmental traits) are also known to affect stability; gait becomes more unstable when environments are more challenging. However, the existing literature has predominately focused on how these factors affect stability based in laboratory settings. These conditions are unlike those experienced in everyday life, and thus we do not know how ecologically valid such studies are.

In this thesis, I focus on how both intrinsic and extrinsic factors affect stability in real-world settings. I do so by assessing gaze and gait behavioural responses to surface complexity (extrinsic factors), visual field loss and reduced cognitive function (both intrinsic factors) when walking. The studies showed that surface complexity in particular, impacted behaviour indicative of stability, whereas young people coped well with intrinsic factors. These findings suggests that either surface complexity has a greater effect than the intrinsic factors tested here on gait stability or that the simulations of intrinsic factors may be inappropriate to simulate age-related conditions when walking outdoors. Furthermore, as no existing measure compares walking surface complexity, I proposed a new metric that included both physical and perceptual measures of the surfaces, acting as a proxy for behavioural change. Our results showed that perceptual measures, in particular, act as a simple metric for surface complexity. I further tested whether perceptual measures may differ based on age of the participant or from first-hand experience compared to images, however this was found to not be the case. As such, surface complexity perception may act a simple

metric to determine behavioural changes which can be determined as effectively when done so remotely and with increased age, despite the well documented age-related behavioural changes. In summary, in this thesis, I show that gaze and gait behaviours are indicative of stability when traversing surfaces of different complexity and perception measures are a good proxy for behavioural change. However, I suggest that outdoor research should be population specific to accurately determine the likelihood of heightened fall risk.

Contents

Chapter One: Introduction

1.1 Introduction: Chapter Overview

Chapter One of this thesis encompasses a review of the relationship between stability and changes in gaze and gait behaviour. These behavioural changes will be discussed in relation to falls and the ways in which intrinsic (individual) and extrinsic (environmental) factors can affect behaviour. It will also discuss how, through modern wearable technology, we have begun to accurately measure behaviours for a wide range of external environmental settings. It will then review the extent and limitations of the current literature and how, from these, I set the aims for this thesis. The introduction concludes with a summary of how each chapter addresses these aims, and the respective outcomes.

1.2 Stability and falls

Moving freely and with ease in the environment requires the brain rapidly processing perceived visual, auditory and tactile information, and setting the appropriate movement response. For young healthy individuals, everyday movements, including gait, are mostly performed semi-automatically, and maintained without cognitive processing or conscious awareness. However, with aging, visual, auditory and tactile acuity decrease (Kenshalo Sr, 1986; Li, Simonsick, Ferrucci, & Lin, 2013; Popescu, et al., 2011). In turn, our ability to achieve "normal" gait is compromised and gait becomes unstable, increasing the risk of a fall. Indeed, the likelihood of a fall increases with age: 30% of people aged 65 and above fall at least once a year, rising to 50% in people aged 80+ (NICE, 2013). Falls are particularly problematic for the elderly, given that bone and muscle degradation imply loss of body strength (Cook, Exton-Smith, Brocklehurst, & Lempert-Barber, 1982; Goodpaster, et al., 2006), leading to a higher risk of injury or even death. If an individual does recover, they are often more frail and more susceptible to subsequent falls (Sri-On, Tirrell, Bean, Lipsitz, & Liu, 2017; Tinetti, Speechley, & Ginter, 1988). Moreover, falls are not only detrimental toward the individual's physical health but also their psychological health (Scheffer, Schuurmans, Van Dijk, Van Der Hooft, & De Rooij, 2008), as well as incurring public healthcare, social, and economic costs (Burns, Stevens, & Lee, 2016; Carroll, Slattum, & Cox, 2005; Katsumata, Arai, & Tamashiro, 2007). The cost of falls to the NHS alone is more than £2.3 billion each year (NICE, 2013). Thus, being able to measure the main determining behaviours of those most at risk of a fall is crucial to provide appropriate preventative interventions.

To identify those most at risk of a fall, we need to assess the stability of individuals whilst walking under normal and challenging conditions. A stable gait can be defined as one that is resilient to perturbations whilst walking and thus does not lead to falls. A number of stability metrics have been proposed; however, no measure has been accepted as a gold standard (as reviewed in Bruijn, Meijer, Beek, & Van Dieën, 2013). One well-studied measure, used as an estimate of stability, is the maximum lyapunov exponent. This measure assesses how much a kinematic signal (body motion at a set point in a gait cycle) diverges from a given intrinsic or extrinsic standard affecting gait. The advantage of this measure is that it can assess kinematic data anywhere in the body, differences being apparent between the young and the elderly during walking at the trunk, ankle and hip (for example; Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Kyvelidou, Kurz, Ehlers, & Stergiou, 2008; Terrier &

Reynard, 2015). However, this measure is best used when assessing short term (localised) changes (e.g. stepping over an obstacle), and may not be suitable for longer term comparisons of gait (Chang, Sejdić, Wright, & Chau, 2010), such as differences when walking on different surface types. An alternative approach, which avoids this measurement's weakness, is to estimate stability from the assessment of multiple sources of behavioural change. In doing so, the researcher can build up a portfolio of the behavioural changes caused by any given intrinsic or extrinsic factors affecting the individual's gait. These behaviours may be assessed in the short term, long term or a combination of the two. To do so, one should consider those behaviours which are considered risky, and thus likely to cause a fall, and also those behaviours which are a response to an individual feeling unstable, described as a "cautious gait" (Pirker & Katzenschlager, 2017). A "cautious gait" is defined by these authors as changes to behaviour in response to heightened perceived risk of a fall. For example, the individual may take shortened, widened steps and walk at a slower gait speed, all as a precaution to a heightened perceived fall risk (Pirker & Katzenschlager, 2017). Crucially, some of these "cautious gait" behavioural changes may have other consequences that increase fall risk. For example, increased leg muscle coactivation (simultaneous contraction of an agonist and antagonist muscle) helps to stabilise the leg when walking (Thompson, Plummer, & Franz, 2018). However, the stiffened leg that results has a reduced range of motion, which in itself is a known risk factor for falls (Chiacchiero, Dresely, Silva, DeLosReyes, & Vorik, 2010; Reddy & Alahmari, 2016). Similarly, there are disagreements between researchers whether behavioural changes are indeed example of a "cautious gait". For instance, an increase in mediolateral (side-to-side) variation of the body when walking is usually considered risky behaviour that increases fall risk (as reviewed in Osoba, Rao, Agrawal, &

Lalwani, 2019), but some researchers have stated that an increased mediolateral variation in steps widens the range of underfoot proprioceptive information (Kent, Sommerfeld, Mukherjee, Takahashi, & Stergiou, 2019; Wurdeman, Huben, & Stergiou, 2012). Thus, such behaviour may be considered a "cautious gait" response. Regardless of whether the behavioural response is an intentional one or not, these behaviours do indicate a deviation from "normal" gait and can help to identify instability when walking.

A "normal" gait for young individuals involves the position of the centre of mass (CoM), the point in the body where there is an equal distribution of weight, fluctuating like an inverted pendulum as the individual walks. In this analogy, the stance leg behaves as the inverted pendulum, moving the CoM in an arc, while the swing leg moves forward before the heel contacts the ground, and the legs then switch roles. In turn, the CoM path shifts towards the leg in contact with the ground at the single-support phase. This movement is shown for one gait cycle (between adjacent double support phases of the same leg) in **Figure 1**. In doing this, the body is propelled forward and the work load of leg muscles is reduced. However, with age, the normal movements of the CoM are disrupted, affecting the gait cycle. For example, older individuals have a decreased mediolateral CoM acceleration throughout the gait cycle and rely less on the trailing limb to propel the body forward during the double support phase of gait, compared to young individuals (Hernández, Silder, Heiderscheit, & Thelen, 2009). Other studies have similarly shown adaptation to gait, including reduced joint motion at the ankles and decreased step lengths (Hageman & Blanke, 1986; JudgeRoy, Davis III, & Õunpuu, 1996). These adaptations increase the time spent in the double support phase of walking, thought to be a response adopted to increase feelings of stability. Despite this, these adaptations are less effective at moving the body forward, which in turn disrupts the normal movement of the CoM. Thus, overall stability *decreases* which in turn may increase fall risk.

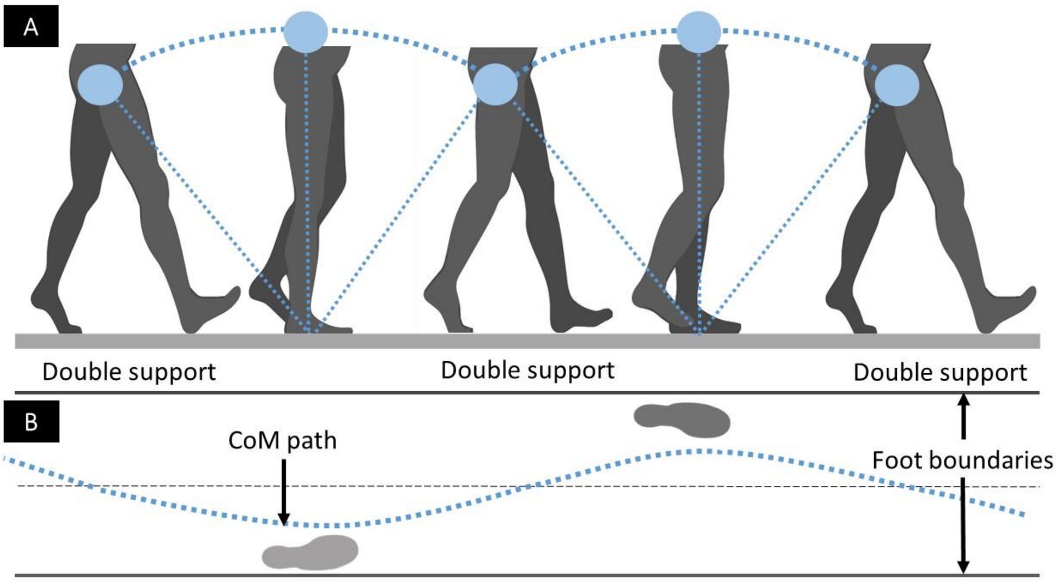

Figure 1: (**A**) A schematic showing the inverted pendulum centre of mass (CoM) movement for one gait cycle (between adjacent double support phases for the same leg). The CoM (blue circle) fluctuates like an inverted pendulum, reaching a maximum vertical position at the single support phase and a minimum position during the double support phases. (**B**) A diagram of the CoM path during one gait cycle. The CoM path remains within the foot boundaries for a normal gait cycle, reaching a maximum lateral position at the single support phases and crossing the midline during the double support phases of gait.

1.2.1 Extrinsic factors affecting stability and fall risk

Determining stability using the inverted pendulum analogy of walking is useful, but as it only explains passive movements, it is unlikely to be fully accurate over complex surfaces. Complex surfaces (e.g. ramps, irregular surfaces, compliant surfaces etc.) are likely to require additional responses (e.g. increased muscle or cognitive input) to maintain stability whilst walking. These surface types are most commonly found outdoors, where the majority of falls occur (Li, et al., 2006). Despite this, most research is conducted indoors and guidelines on fall prevention are limited to indoor environments (Panel on Prevention of Falls in Older Persons & Society, 2011). This is perhaps unsurprising given the complexities of conducting experiments outdoors compared to laboratory conditions. Furthermore, laboratory experiments allow for greater experimental control and, until recently, fixed laboratory equipment had greater accuracy of measured behaviours compared to those obtainable using portable, wearable sensors. More recent laboratory studies have begun to bridge the gap in outdoor fall research, conducting studies under more accurate representations of outdoor settings. This has included analysis of gait over artificial irregular surfaces, compliant surfaces and mixed surface types (Curtze, Hof, Postema, & Otten, 2011; MacLellan & Patla, 2006; Merryweather, Yoo, & Bloswick, 2011). Replicating outdoor settings in laboratory conditions has revealed additional differences in gait behaviour between the young and elderly that were not apparent over smooth surfaces. For instance: irregular surfaces were associated with increased step width variability, reduced speed and decreased step length in older people when compared to the young (Hylton B Menz, Stephen R Lord, & Richard C Fitzpatrick, 2003; Thies, Richardson, & Ashton-Miller, 2005). Such studies are particularly beneficial given that the heightened fall risk of older populations over more complex surfaces can be minimised in simulated outdoor settings using protective clothing and safety harnesses. However, it should be noted that simulations of more complex surfaces in a laboratory rarely test all other environmental factors that we contend with then walking outside, including the weather, traffic and changeable lighting.

One other difficultly in simulating walking akin to that outdoors is replicating the vast variety of walking surfaces. For more complex surfaces, previous studies have typically focused on one type of complex surface, including uneven, compliant or sloped surfaces (Merryweather, et al., 2011; Morgan, Hafner, & Kelly, 2017; Thies, et al., 2005), with few studies comparing multiple surface types in the same study (Marigold & Patla, 2007, 2008a). However, this is unlikely to replicate conditions most people encounter in their daily lives; pedestrians possibly walking over several different surface conditions within the space of a few minutes. An important factor currently missing in the literature is a metric to compare different surface conditions. The existing literature mostly relies on characterising surfaces from descriptions or from differing behaviours assessed from a relatively small sample size of their tested population group (e.g. Marigold & Patla, 2007; Matthis & Fajen, 2014). As such, comparisons between different studies is not possible. A potential solution to this would be to determine the physical measures of surfaces. A similar metric does exist for determining road surface complexity (Sayers, 1984), however, given that a large component of the metric is based on assessment of the vehicle, this metric is not suitable for walking surfaces. Moreover, any such metric for walking surfaces should consider how surfaces may be perceived as more complex for certain population groups. For example, given that injury risk from a fall for older individuals is higher than that of the young, (Sterling, O'connor, & Bonadies, 2001), surfaces that constitute as "complex surfaces" for some population groups may differ to others.

As well as complex surfaces, falls are particularly common when changing level, including over stairs, steps and curbs (Nevitt, Cummings, & Hudes, 1991). Level changes require an increased range of motion as well as muscle activity to safely traverse (Nadeau, McFadyen, & Malouin, 2003), both of which are known to be adversely affected with age (Grimmer, Riener, Walsh, & Seyfarth, 2019; Reeves, Spanjaard, Mohagheghi, Baltzopoulos, & Maganaris, 2008). Given these age-related behavioural changes, several studies have determined how the behaviour of older individuals differs to that of the young in respect to traversing stairs. For example, when traversing stairs, older individuals exhibit: an increased mediolateral CoM velocity, greater swaying at the hips and more erroneous foot clearances of stairs (Begg & Sparrow, 2000; Bosse, et al., 2012; Novak & Brouwer, 2011). As these behavioural changes increase fall risk, it is important to consider whether certain interventions could lower the chances of a fall. A study by Hamel, Okita, Higginson, and Cavanagh (2005) investigated stair negotiation under different lighting conditions. Their study showed that under low lighting levels, older individuals, unlike the young, do not increase foot clearance as a precautionary measure. However, Foster, Hotchkiss, Buckley, and Elliott (2014) demonstrated that highlighting stair edges increases foot clearance, even for those with simulated age-associated visual decline. Therefore, stairs undoubtedly cause gait behavioural changes associated with heightened fall risk, but vision-associated interventions (including lighting and contrast enhancement from highlighting stair edges) may be vital in diminishing this risk.

1.2.2 Intrinsic factors affecting stability and fall risk

As well as changes in the musculoskeletal system shown to affect gait behaviour, gait is also affected by changes in sensory inputs, including those from visual health decline. Indeed, visual health deteriorates with age, with one in five people aged above 75 suffering from either full or partial sight loss (Sinclair, Ryan, & Hill, 2014). Furthermore, visual acuity, field size and contrast sensitivity deteriorate, all of which are associated with an increased fall risk (Black, Wood, & Lovie-Kitchin, 2011; de Boer, et al., 2004; Lord & Dayhew, 2001). To investigate how age-associated visual impairments impact stability, studies have assessed how older individuals with impairments differ in their gait behaviours to young individuals (for example see, Kunimune & Okada, 2019; Saucedo & Yang, 2017). Alternatively, studies have inferred stability in these individuals from changes in gaze behaviour. For example, high fall-risk older individuals are more likely to prioritise future steps when walking, shifting gaze sooner from ongoing movements and thus are more likely to misplace their feet in more proximal steps (Chapman & Hollands, 2006). However, given that older individuals may have co-morbidities which affect movement, findings from these studies may not be due to the visual impairments alone. To address this possibility, researchers have simulated visual impairments in otherwise healthy young individuals. For instance, simulated visual acuity loss (blurred vision) in the young was associated with reduced gait speed, higher foot clearance and prolongation of gaze toward the floor when walking (Freedman, Achtemeier, Baek, & Legge, 2019; Heasley, Buckley, Scally, Twigg, & Elliott, 2004; Novak & Deshpande, 2014; Zult, Allsop, Timmis, & Pardhan, 2019). Similarly, simulated vision loss (blocked vision) was associated with reduced gait speed, shorter steps and a greater proportion of gait spent in the double support phase (Hallemans & Aerts, 2009). Peripheral vision from the lower visual field is likely to be particularly important, aiding information from surfaces underfoot. Indeed, older individuals with a loss of their lower visual field tend to suffer from an increase in falls (Black, et al., 2011). Notably, simulations of blocked lower visual field in the young have produced similar gaze patterns whilst walking to that of individuals with age-related vision loss (Krishnan, Cho, & Mohamed, 2017). Therefore, diminished vision health unquestionably contributes to fall risk and gaze behaviour is a useful measure of stability whilst walking.

Visual health is particularly important for stability when navigating more complex environments. Qualitative research has identified different environmental factors that increase fall risk, including more complex environments such as uneven surfaces, tripping hazards and slippery surfaces (Nyman, Ballinger, Phillips, & Newton, 2013). Experimental studies have supported these findings. For example, uneven surfaces were associated with young people increasing their number of eye fixations on planned future foot placements as well as on transitional areas between different surface types (Marigold & Patla, 2007). Fixating towards underfoot surfaces is likely to aid stability, allowing appropriate adaptations of the body to occur with each step. However, high-risk older individuals shift their gaze from future foot placements sooner, and are more likely to miss step targets (Chapman & Hollands, 2006). These erroneous behaviours can be corrected; interventions of gaze training techniques have been shown to be effective at reducing stepping error (Young & Hollands, 2010). Other studies that have "corrected" risky behaviour under complex conditions have used virtual reality (VR) to improve gait performances (Mirelman, et al., 2011). VR is particularly beneficial for older individuals as studies can be done using safety harnesses in laboratory conditions whilst allowing natural walking akin to that in everyday life (Borrego, Latorre, Llorens, Alcañiz, & Noé, 2016).

As well as complex surfaces underfoot, "cluttered" environments may pose similar problems. These environments, typically outside, often have visual and auditory distractions that are often moving in the environment, such as pedestrians, vehicles and fixed distractions such as street furniture. These may impose visual difficulties for the elderly due to their inability to contrast objects effectively against one another given age-associated visual decline (as reviewed in Harwood, 2001). Moreover, visually complex environments (e.g. supermarkets and shopping malls) and moving visual environments have a greater effect on older individuals with vestibular and anxiety disorders compared to young individuals (as reviewed in Redfern, Yardley, & Bronstein, 2001). One common example of an often visually complex environment is pedestrianised crossings. At crossings, the gaze and gait behaviours of older individuals differs to that of the young. Older individuals cross more slowly with gaze focused downwards for longer, thus paying less attention to surrounding traffic (Avineri, Shinar, & Susilo, 2012; Zito, et al., 2015). Given that older individuals typically walk more slowly than the young, the time given by traffic signals for crossing may be insufficient. Studies have shown that older individuals are less likely to cross safely during the pedestrianised signal time (Asher, Aresu, Falaschetti, & Mindell, 2012; Hoxie & Rubenstein, 1994). Moreover, the oldest individuals are twice as likely to be unable to cross whilst completing a cognitive task (Eggenberger, Tomovic, Münzer, & de Bruin, 2017). Thus, given that older individuals are at greater risk of a fall in general, imposing an additional task (e.g. walking within a sufficient time duration), places older individuals at greater fall risk in these visually complex locations.

As walking is generally more difficult with age, as evidenced for example by the adoption of a cautious gait (as reviewed in Li, Bherer, Mirelman, Maidan, & Hausdorff, 2018), it is likely that those processes that ensure stable walking will need additional cognitive input. Indeed, older individuals with cognitive impairments walk with a more cautious gait and are at greater risk of a fall compared to those without such impairments (Hausdorff, Edelberg, Mitchell, Goldberger, & Wei, 1997; Holtzer, Verghese, Xue, & Lipton, 2006). Furthermore, given that in everyday life we walk whilst completing simultaneous tasks that require cognition, including navigating to destinations, talking to others or listening to music, the ability to complete both a secondary task and to walk safely is likely to be compromised in older individuals. The effect of completing a secondary task on gaze and gait performance can be determined from the dual-task cost (for example see; Beauchet, Dubost, Aminian, Gonthier, & Kressig, 2005; Ellmers, Cocks, Doumas, Williams, & Young, 2016). Dual task costs are defined by the following equation:

$$Dual\ task\ Cost(\%) = 100\ \times \frac{dual\ task\ perfomance - single\ task\ performance}{single\ task\ performance}$$

This calculation can either assess the cost for the performance of the secondary task itself (mobile phone texting accuracy, reaction time etc.) or assess the performance of behaviour metrics (gait speed, stride time etc.). For instance, when walking outside, older individuals have greater dual-task costs (i.e. worse performances) on texting speed and accuracy, but also gait speed, acceleration magnitude and gait variability (Krasovsky, Weiss, & Kizony, 2018; Takeuchi, Mori, Suzukamo, Tanaka, & Izumi, 2016). When determining the dual task cost on the secondary task, the performance may depend on the task itself. Previous research has assessed numerous types of cognitive tasks including memory tasks (Lindenberger, Marsiske, & Baltes, 2000; Springer, et al., 2006), numerical tasks (Agner, Bernet, Brülhart, Radlinger, & Rogan, 2015; Montero-Odasso, et al., 2009) or motor control tasks (Beurskens & Bock, 2013; Hunter, Divine, Frengopoulos, & Odasso, 2018). Indeed, studies have shown different gait responses dependent on the task given, (see for example Nordin, Moe-Nilssen, Ramnemark, & Lundin-Olsson, 2010). Thus, given the age-related decline of both cognitive and motor abilities, the completion of a secondary task and/or the stability of walking are likely to deteriorate with age, depending on the type of task and the environment given.

1.3 Wearable technology

This section looks at how the advances in wearable technology have influenced the assessment of gaze and gait behaviour. Specific detail will be given on how different behaviours are assessed and the reliability of these technologies.

Understanding our environment visually may prove beneficial for interventions aimed at reducing fall risk, not only as vision is known to deteriorate with age but as more visually complex environments are known to change gait behaviour (as reviewed above). To understand this, we can assess how the environment brings about changes to our gaze behaviour. Gaze behaviour can either be assessed from eye movements, head movements or a combination of the two. Eye movements may be recorded using eye trackers which track pupillary movement (via infrared cameras directed towards the eyes) and project this in relation to the world view (recorded from a camera directed toward the environment). An example frame taken from an eye tracker output is shown in **Figure 2A**. Using both cameras, eye trackers can indicate where in the environment the person is looking. Eye tracking has been used in a wide array of studies, including whilst driving, in cognitive development and even determining differences between professionals' and trainees' observational assessments of gait abnormalities (Aslin, 2012; Hayashi, Aono, Fujiwara, Shiro, & Ushida, 2020; Kunishige, et al., 2019). The use of eye trackers can highlight the key aspects of the environment that are used to maintain gait stability and how this may change as we age. Head movements have been recorded using several different methods, including from sensors recording inertia data at the head, (Matthis, Yates, & Hayhoe, 2018), movements recorded from head mounted video footage ('t Hart & Einhauser, 2012) and simply through observation (Avineri, et al., 2012). An example experimental set-up using kinematic markers attached to the head potentially used to calculate head movement is shown in **Figure 2B**. Understanding head movement is useful for gaze analysis, providing a simple method by which to determine where the person is looking. Here, following Tomasi, Pundlik, Bowers, Peli, and Luo (2016), I define gaze from the combined eye and head movements. A diagram showing how I defined vertical gaze angle is shown in **Figure 2C**. This approach of combining eye and head movement provides a more accurate measure of understanding where the person is looking, especially given that when walking outside less than 60% of gaze is brought about by eye movements, the rest resulting from movements of the head (Tomasi, et al., 2016).

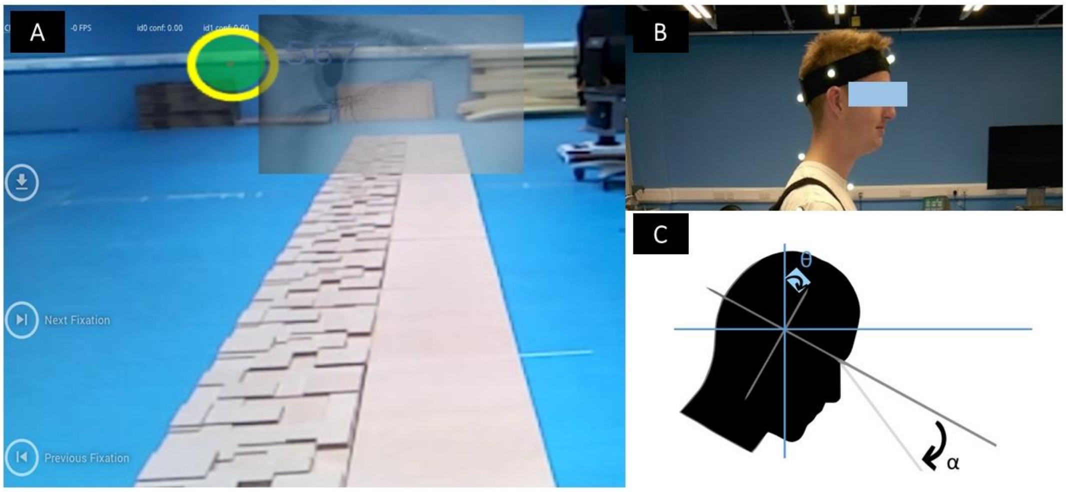

Figure 2: (**A**) A frame from the Pupils eye tracker (Kassner, Patera, & Bulling, 2014), showing how input from the eye and environment camera are used to calculate eye movements. (**B**) One method used to measure head movements: here, head movement is calculated from infra-red camera recordings of the movement of kinematic markers attached to the participant's head. (**C**) A diagram showing how vertical gaze angle is calculated from combined eye and head movements. In this example, gaze angle is made up of the combination of vertical eye angle (α) and head pitch angle (θ).

Another major progression in the analysis of gaze and gait behaviours has come from wearable devices assessing body movements through the placement of different sensors on the body. Inertia measurement unit sensors (IMUs) incorporate accelerometers, gyroscopes and magnetometers to measure the acceleration, velocity, orientation and gravitational forces at particular locations on the body. At different locations, different gait parameters can be measured. For example, at the ankle IMUs can be used to measure gait events, gait speed and joint angles (Seel, Raisch, & Schauer, 2014; Storm, Buckley, & Mazza, 2016; Storm, Nair, Clarke, Van der Meulen, & Mazza, 2018), at the back IMUs can measure CoM movements, gait symmetry and step times (Johnston, Patterson, O'Mahony, & Caulfield, 2017; Li, Xu, & Cheung, 2016; Zhang, et al., 2018), while at the head we can measure head angles, head acceleration and gait speed (Matthis, Barton, & Fajen, 2017; H. B. Menz, S. R. Lord, & R. C. Fitzpatrick, 2003; Zihajehzadeh & Park, 2017).

The advancement of sensor technologies has allowed gaze and gait analysis, traditionally assessed through wall and floor mounted eye trackers, motion capture cameras and force plates, to be accurately measured by far smaller, wearable devices. Many of these devices have the potential to be used outside in motion, however, before extensive utilisation, sensors should be validated against fixed sensors to ensure reliability. Few studies have determined the accuracy of gaze behaviour from eye trackers when walking, likely due to the difficulties in testing accuracy of gaze in a moving environment. However, one recent study showed eye trackers to accurately interpret eye fixations regardless of gait speed (Serchi, Peruzzi, Cereatti, & Della Croce, 2016). In contrast, more studies have established the feasibility of using body-mounted IMUs to determine gait parameters. IMUs have been tested for accuracy at several places on the body, including at the head and at the hips (Jasiewicz, Treleaven, Condie, & Jull, 2007; Saber-Sheikh, Bryant, Glazzard, Hamel, & Lee, 2010), with errors being generally low. Similarly, gait speed and gait events can be accurately measured from IMUs at the ankle when compared to pressure insole data and treadmill data, including when walking over slopes or over ground surfaces (Li, Young, Naing, & Donelan, 2010; Storm, et al., 2016). Validating these sensors over a wide range of conditions (surface type, lighting etc.) should be conducted before mass utilisation. However, every effort should be made to encourage sensor use outside of traditional laboratory-based settings to further our understanding of gait in real-world settings.

1.4 Summary and thesis aims

Whilst the extant literature has improved our understanding of gaze and gait behaviour associated with decreased stability when walking, more research is required for elucidation of the associations in those environments that are identified as high fall-risk. Improvement in the capability of, as well as reductions in the size of wearable technologies has the potential for major developments in this field, however most studies have not assessed eye and head movements simultaneously when walking in more complex settings. Commonly, measures of gaze do not incorporate an accurate assessment of gaze and only a limited number of publications have assessed gaze or gait behaviour in high fall-risk settings (for example see 't Hart & Einhauser, 2012; Matthis, et al., 2017), however, environmental settings have varied substantially between studies. Moreover, there are no existing metrics to compare different surface settings, studies relying on author descriptions of surface types only. These descriptions may change based on each individual's perception.

Peripheral vision and cognition, likely to play an essential role in the successful navigation of more complex environments, are known to deteriorate with age. However, no study to date has obtained detailed information on the behavioural changes occurring during more complex walking conditions when the lower peripheral visual field and cognition are impaired. Furthermore, it remains unknown whether these impairments affect behaviours differently dependent on the character of the environment. Studies which simulate lower peripheral visual field loss and cognition decline in young, healthy individuals are beneficial in that they can exclude the effects of age-associated co-morbidities (for example see Marigold & Patla, 2008b; Nordin, et al., 2010), but researchers have yet to test these results in more ecologically valid settings. If simulations could be validated across different environmental settings, future studies could use these to help develop appropriate preventative interventions, potentially reducing the risk and prevalence of falls.

On the basis of these identified gaps within the literature, I set out the below aims to be investigated in the thesis:

- To assesses head movements independently from eye movements to understand how surface complexity influences gaze, and to see how this relates to changes in gait (Chapter 2).
- To measure objective properties of walking surfaces, using a variety of both physical and perceptual metrics to try to categorise surfaces with respect to assessed walking behavioural change (Chapter 3).
- To assess how a blocked lower visual field would impact gaze and gait behaviour and assess whether there is an over-additive interaction between a blocked lower visual filed and an increase in surface complexity on behaviour (Chapter 4).

- To assess how a blocked lower visual field and a cognitive task, independently and in combination, affect gaze and gait behaviour over surfaces of different complexity (Chapter 5).
- To assess how age and experience may affect perception of different surfaces (Chapter 6).

In conducting studies to address these aims, we can further our understanding of locomotion when outdoors and determine the key determinants that lead to increased fall risk.

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Chapter Two: Assessing how gaze and gait speed are influenced by surface complexity

In this chapter, I address how an improved measure of gaze, calculated from combined eye and head pitch angle, as well as gait speed, differed when walking over surfaces of different complexity, both in the laboratory and outdoors. Previous research has determined how surfaces of increased complexity change eye and gait behaviours. However, the aim in this chapter was to include movements at the head when calculating gaze and to then elucidate how eye and head pitch angles contribute to overall gaze. Furthermore, I wanted to determine whether the contributions to gaze, from eye and head pitch, and gait speed change over surfaces of different complexity.

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The primary author conceived and designed the experiments, conducted the experiments, analysed the data, prepared the figures and tables, authored and approved the final draft.

2.1 Abstract

Background: Most research investigating the connection between walking and visual behaviour has assessed only eye movements (not head orientation) in respect to locomotion over smooth surfaces in a laboratory. This is unlikely to reflect gaze changes found over the complex surfaces experienced in the real world, especially given that eye and head movements have rarely been assessed simultaneously.

Research question: How does gaze (eye and head) angle and gait speed change when walking over surfaces of different complexity?

Methods: In this exploratory study, we used a mobile eye tracker to monitor eye movements and inertial motion sensors (IMUs) to measure head angle whilst subjects (n=11) walked over surfaces with different complexities both indoors and outdoors. Gait speed was recorded from ankle IMUs.

Results: Overall, mean gaze angle was lowest over the most complex surface and this surface also elicited the slowest mean gait speed. The head contributed increasingly to the lowering of gaze with increased surface complexity. Less complex surfaces showed no significant difference between gaze and gait behaviour.

Significance: This study supports previous research showing that increased surface complexity is an important factor in determining gaze and gait behaviour. Moreover, it provides the novel finding that head movements provide important contributions to gaze location. Our future research aims are to further assess the role of the head in determining gaze location during locomotion across a greater range of complex surfaces to determine the key surface characteristics that influence gaze during gait.

2.2 Introduction

Our ability to understand how people walk through their environment should be informed not only by assessment of their gait but by understanding the visual information available to them. Visual information is particularly important when environments are more complex, requiring increased planning to maintain stability whilst walking. For example, spatial and temporal visual information has been shown to be essential for correct foot positioning over complex surfaces, both inside and outside of the laboratory (Matthis, Barton, & Fajen, 2017; Matthis & Fajen, 2014; Matthis, Yates, & Hayhoe, 2018). Complex surfaces increase fall risk for all age groups as a result of poor stability (Nyman, Ballinger, Phillips, & Newton, 2013; Talbot, Musiol, Witham, & Metter, 2005). Therefore, an increased understanding of how vision and gait are impacted by different surfaces is important to help to understand and prevent falls.

Research investigating gait and gaze often uses terminology inconsistently. Here, we will use 'complex' to refer to all non-smooth surfaces. These include surfaces with slope changes (Merryweather, Yoo, & Bloswick, 2011), inconsistently spaced foot targets (Matthis & Fajen, 2014; Patla & Vickers, 2003), uneven surfaces (Thies, Richardson, & Ashton-Miller, 2005) and combinations of these features (Marigold & Patla, 2007, 2008). Smooth surfaces here are taken to include even, horizontal surfaces in laboratories (Marigold & Patla, 2007), on walkways (Graci, Elliott, & Buckley, 2010) and outside (Storm, Buckley, & Mazza, 2016). Lastly, while gaze is often used by researchers to refer only to eye movements, here we define gaze as the orientation of the eye in a world reference frame. Gaze thus combines eye-in-head movements and head-in-world movements, which we measured using an eye tracker and an inertia measurement unit sensor (IMU) respectively.

Most gait research uses a smooth, horizontal, hard laboratory floor. However, some laboratory-based studies have started to address how conditions more representative of real-world surfaces may impact our behaviour. These studies have not, though, produced consistent findings. For example, Menant, Steele, Menz, Munro, and Lord (2009) found that gait speed decreased over complex surfaces, but this finding was not supported by the work of Thies, Richardson (Thies, et al., 2005). These differences may have arisen because there are no standards for defining complex surfaces in terms of roughness, slope, etc. In contrast to studies of gait, studies investigating gaze during walking have shown a clearer consensus. Compared to smooth surfaces, complex surfaces have been shown to cause eye movements to be increasingly directed to the ground, to lead to increased numbers of fixations, and to require visual information from at least two steps ahead for safe and efficient locomotion (Marigold & Patla, 2007; Matthis, Barton, & Fajen, 2015; Matthis & Fajen, 2014; Matthis, et al., 2018).

Crucially, it is not known whether laboratory simulations accurately represent the surfaces over which we typically walk in everyday life. An alternative, and more ecologically valid, approach to using mixed surface conditions inside the laboratory is to conduct experiments outside. 't Hart and Einhauser (2012) assessed gaze for individuals walking outdoors on irregularly placed steps and a smooth road. They reported that their complex surfaces caused individuals to lower both their eyes and head. The eyes lowered more than the head, suggesting that the eyes served more immediate demands when walking. Note, though, that this study only indirectly measured head movements by inferring them from the output of the scene view camera attached to the eye-tracker. Thus, we do not yet have an accurate understanding of how the head affects overall gaze.

Although the results of 't Hart and Einhauser (2012) suggest that the head plays an important role in altering gaze when traversing complex surfaces, few other studies have investigated the importance of head movements, independent of eye movements, in contributing to overall gaze. For example, Matthis and Fajen (2014) & Marigold and Patla (2007) only considered eye movements during walking over complex surfaces. Other studies have inferred head movement from movements of the world camera attached to the eye tracker ('t Hart & Einhauser, 2012; Elloumi, Treuillet, & Leconge, 2013). In the present study we follow Matthis, et al. (2018) using an alternative approach that allowed us to measure head movements independent of the eye tracker whilst walking over complex surfaces. This methodology to calculate gaze has been previously used for tasks other than walking over complex surfaces, for example see (Fang, Nakashima, Matsumiya, Kuriki, & Shioiri, 2015; Land, 1992). Head movements are particularly important to consider given that weakened musculoskeletal health, including age associated declines, might limit head movement, and this, in turn, could impact gaze. Tomasi, Pundlik, Bowers, Peli, and Luo (2016) assessed head movements, using IMUs, whilst also tracking eye movements. They found that over 40% of gaze movement was due to head movements when walking outdoors. This study did not, though, measure other behaviour changes which are also likely to be important to understanding the relation between locomotion and gaze behaviour, such as speed of locomotion and changes in stride length or timing. Moreover, Tomasi, et al. (2016) only analysed head yaw (left to right, horizontal movement), whereas head pitch (up and down, vertical movement) is likely to be more important when traversing non-smooth surfaces ('t Hart & Einhauser, 2012). Common sense would dictate that movement of the eyes to change vertical gaze orientation are more energy efficient than movement of the head, which requires the activation of more and larger, muscles for the same effect on gaze location. However, to the authors' knowledge, no study has accurately assessed eye angle and head angle when walking over complex surfaces. Thus, it remains unclear how eye and head angle contribute to gaze when walking over different surfaces.

On the basis of the above we believe it is important to independently assess head as well as eye movements to understand how surface complexity influences gaze, and to see how this relates to changes in gait. As an initial step, in this exploratory study, people walked in a straight line on four horizontal surfaces at self-paced speeds. We measured changes in vertical eye angle and head pitch angle, as well as the gait speed of participants. Here, we focus on presenting results for mean values across a trial walk for eye angles, head pitch angles, gaze (combined eye and head pitch) angles and gait speed, as our aim was to compare overall performances across different surface complexities. In future work we aim to conduct more fine-grained analyses of short term, step by step changes in the relation between eye and head pitch angles and gait. For eye and head angle, only vertical change was assessed as horizontal movements are unlikely to be associated with maintaining stability during straight line walking. Thus, in summary, we assessed how eye and head movements independently contribute to gaze, and how this relates to changes in gait speed during locomotion over surfaces of different complexity.

2.3 Methodology

2.3.1 Participants

11 healthy adults (7 male, mean ± SD; age = 24.6 ± 3.5 years; height = 173 ± 6.5cm) were recruited for this exploratory study. Data from 9 more participants was

collected but was not used due to a malfunction of the inertia sensors (both the gyroscopic and accelerometric data recorded for these participants produced extreme values, far exceeding the normal range in all trials). For ease of recording data with the eye tracker, only participants who did not require glasses for everyday walking were selected. No participant had an injury or impairment that affected their gait or vision.

2.3.2 Data Collection

Ethical approval for the study was obtained from the University of Liverpool's Ethics Committee (REF: 1900). Two IMU sensors (Delsys TRIGNO™ IM, Boston, MA, USA) were positioned on the participant. Each sensor consisted of a 3-axis accelerometer, gyroscope and magnetometer, recording at 148Hz. One IMU was positioned close to the midline of the forehead to calculate head pitch angle using gyroscopic data. The second IMU was positioned above the lateral malleoli on the left shank and was used to calculate gait events. Participants wore an Arrington Research ViewPoint (Scottsdale, Arizona, USA) eye tracker that recorded pupil movement at 60 Hz and a scene camera that recorded the participant's view of the environment that recorded at 30Hz. Eye angles in the vertical direction were calculated in order to calculate how far ahead on the ground participants were looking as they walked.

2.3.3 Protocol

The eye-tracker was calibrated prior to each data collection session. Eye movements were calculated based on the dimensions on the screen used in the calibration, see supplementary material (2.7.1). Participants then walked ten times over four different surfaces so they each completed 40 trials in total. The surfaces comprised an uneven, indoor, and a flat, indoor surface, both in a gait laboratory, and then a paved, outdoor, and a cobbled, outdoor surface, both on the university campus

(**Figure 1A-D**). The indoor, flat surface (13.20m long) consisted of eleven 18mm thick medium density fibreboards (MDF) panels. The indoor, uneven surface was identical except that each panel had an array of blocks of 9mm thick MDF on top of the base layer to give an uneven surface with a maximum height range of 27mm. Each panel had the same block design, with blocks spaced to prevent participants from easily targeting footfalls whilst walking. The outdoor, paved surface (16.60m long) comprised paving stones (60 x 60cm) whilst the outdoor, cobbled surface (15.70m long) comprised of setts. All surfaces were long enough to ensure participants could achieve a steady state of walking (Najjar, Iman-Eini, & Moeini, 2017).

Participants walked over a wooden obstacle (61cm wide x 29.5cm deep x 10cm high) placed at either the start or end of each surface. This obstacle was intended to increase surface complexity and thus to influence behaviour. However, the location of this obstacle (start versus end) did not show a strong or clear relationship with either gaze angle or speed across any of the four surfaces so this manipulation was not included in the analysis presented here.

On each trial participants were instructed to begin by looking straight ahead whilst standing still in front of each surface for three seconds, then to walk at a self-determined, comfortable speed along the surface before looking straight ahead whilst standing still at the end of the surface for three seconds. No instructions were given regarding head or eye movement when walking.

Figure 1: Images showing the four surfaces: (**A**) indoor, flat, (**B**) outdoor, paved (**C**) outdoor, cobbled and (**D**) indoor, uneven. To estimate surface roughness, we used a clinometer to take 20 measurements of the height change between a pair of points that were 15cm apart. This was done at 30cm intervals along each surface. The mean (± SD) height change was 1.8° (±0.5°) for the indoor, flat surface, 1.9° (±0.5°) for the outdoor, paved surface, 2.5° (±1.9°) for the outdoor, cobbled surface and 7.5° (±2.6°) for the indoor, uneven surface.

2.3.4. Data Analysis

Mean eye angle and head pitch angle were calculated for each trial of each surface for all participants. For the raw vertical gyroscopic data used to determine head pitch angle, a low pass, 10Hz fourth-order Butterworth filter was used to reduce noise. The effect of drift was removed using gyroscopic data taken from the period when the participant remained still at the start and end of each trial (following Takeda, et al. (2014)). The gyroscopic data (in degrees per second) was then numerically integrated over the trial to give head pitch angle. The supplementary material (2.7.2) describes a check of the accuracy of this method. The vertical eye movements were converted into angular data. A head pitch angle of 0° was defined as the average head orientation at the beginning and end of each trial when the participant remained still whilst looking straight ahead. To avoid the influence of starting and stopping, the walking data was trimmed to remove the first two and last two strides from each trial. Every 1/60s during each trial the eye angle and head angle were summed and these sums were then averaged across the trial to calculate gaze (combined eye and head pitch) angle for that trial. The relative frequency distribution of eye, head pitch and gaze angles for each surface were also calculated. This measurement follows Foulsham, Walker, and Kingstone (2011) in calculating the frequency of recorded angles for each surface in bins of 5° relative to zero. In effect this distribution shows the variance of eye and head movement during the trial. Only eye angles that were within the normal range expected based on previous reports (Lee, Kim, Shin, Hwang, & Lim, 2019) and from our own validation study, see supplementary material (2.7.3), were included.

Gait speed was calculated using the shank IMU to estimate the shank ankle and then combining this with integrated accelerometery data (following Li, Young, Naing, and Donelan (2010)). As this method has only been tested over smooth surfaces, we checked its accuracy over the most complex surface, the indoor, uneven surface, as detailed in the supplementary material (2.7.2).

Repeated-measures ANOVAs were conducted on the participant's mean eye angles, head pitch angles and gaze angles. The factor of surface had four levels: flat, paved, cobbled and uneven. Correlations were calculated between eye angle and head pitch angle every 1/60s of the trial for all participants. We then conducted t-tests for each surface to compare the mean correlation across participants to a no correlation value (zero). Zero correlation would suggest that there was no relation between eye angle and head pitch angle for that surface. A repeated-measures ANOVA was conducted for the participant’s mean gait speed with a factor of surface. Finally, correlations were calculated between mean speed and mean eye angle, mean head pitch angle, and mean gaze, followed by t-tests for each surface to compare the mean correlation across participants to a no correlation value (zero). These correlations were calculated between mean values over a whole trial since speed was calculated across step duration whereas eye, head pitch and gaze angles were calculated every 1/60s.

2.4 Results

2.4.1 Analysis of the orientation of eye, head pitch and gaze (combined eye and head pitch) angles

Comparisons were made between all four surfaces. Mean (± SE) eye (α/red), head pitch (θ/blue) and gaze (grey) angles (°) are shown in **Figure 2**. Surface had a significant effect on gaze angle, $F(3, 30) = 28.34$, $\eta_p^2 = 0.81$, $p=0.003$. Post-hoc Newman Keuls tests ($p < 0.05$) showed gaze to be significantly lower for the indoor, uneven surface compared to the other three surfaces. The contribution to mean gaze angle from head pitch (θ) angle changes were 17% for indoor, flat surfaces; 25% for outdoor, paved surfaces; 35% for outdoor, cobbled surfaces; and 54% for indoor, uneven surfaces. This contribution was calculated as the percentage of the head pitch angle compared with gaze (combined eye and head pitch) angle taken every 1/60s over the course of every trial and then averaged. The average frequency distribution of eye, head pitch and gaze angles over the trial was calculated for each surface, see **Figure 3**. The indoor, uneven surface had a different distribution to the other three surfaces. These other surfaces all had peak head pitch angles close to zero, whereas the indoor uneven surface showed a greater range of head pitch angles. For this surface, head pitch angle was often lowered, with a similar range distribution to that for eye angle.

Gaze (combined eye and head pitch) angle showed a similar distribution to eye angle for all but the indoor, uneven surface where it was generally lower.

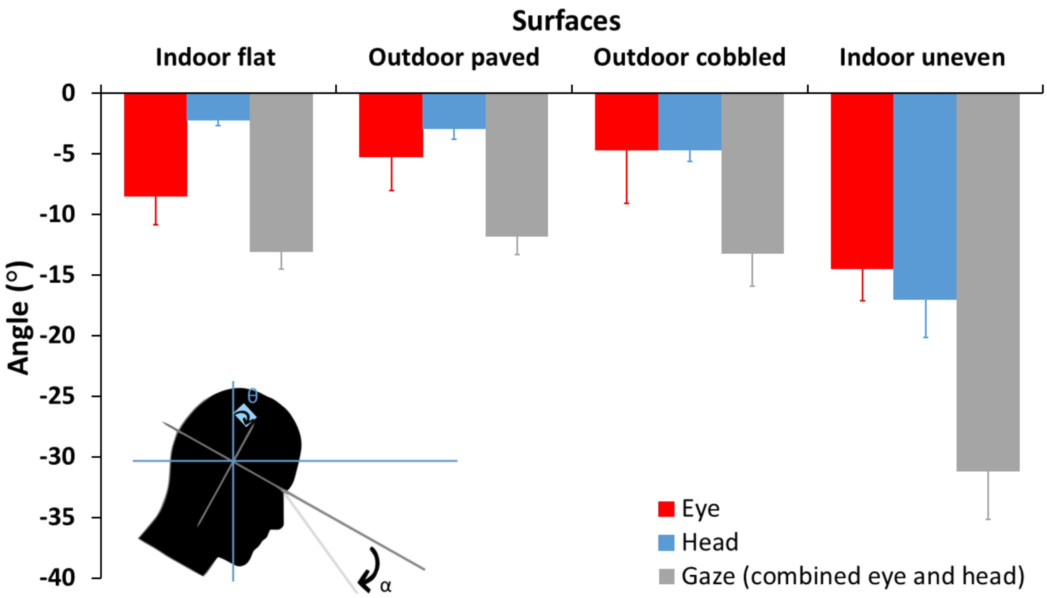

Figure 2: Mean (± SE) eye, head pitch and gaze (combined eye and head pitch) angles (°) for the four surfaces tested: indoor, flat; outdoor, paved; outdoor, cobbled; and indoor, uneven. The inset shows how eye (α/red) and head pitch (θ/blue) angles were measured. Mean gaze (combined eye and head pitch) angle is the mean value of the sum of eye angle and head pitch angle calculated every 1/60s (and not the sum of the mean eye angle and mean head pitch angle).

A one sample t test showed that the correlation between eye and head pitch angle for the indoor, flat (M ± SD = +0.13 ± 0.17*)*, and outdoor, paved surface, (+0.24 ±0.15) were significantly greater than zero (t (10) = 2.46, *p=0.034* and t(10) = 5.63, *p<0.01* respectively*)*. These correlations, albeit weak, suggest that eye and head movements are co-ordinated when walking over these surfaces. The correlations for the indoor, uneven (+0.01 ± 0.17; t(10) = 0.26, *p=0.801)* and outdoor, cobbled (+0.15 ± 0.23; t(10) = 2.12, *p=0.060)* surfaces were not significantly different to zero. As all four correlations were all relatively low, this suggests that eye angle and head pitch angle both contribute distinct information about gaze angle.

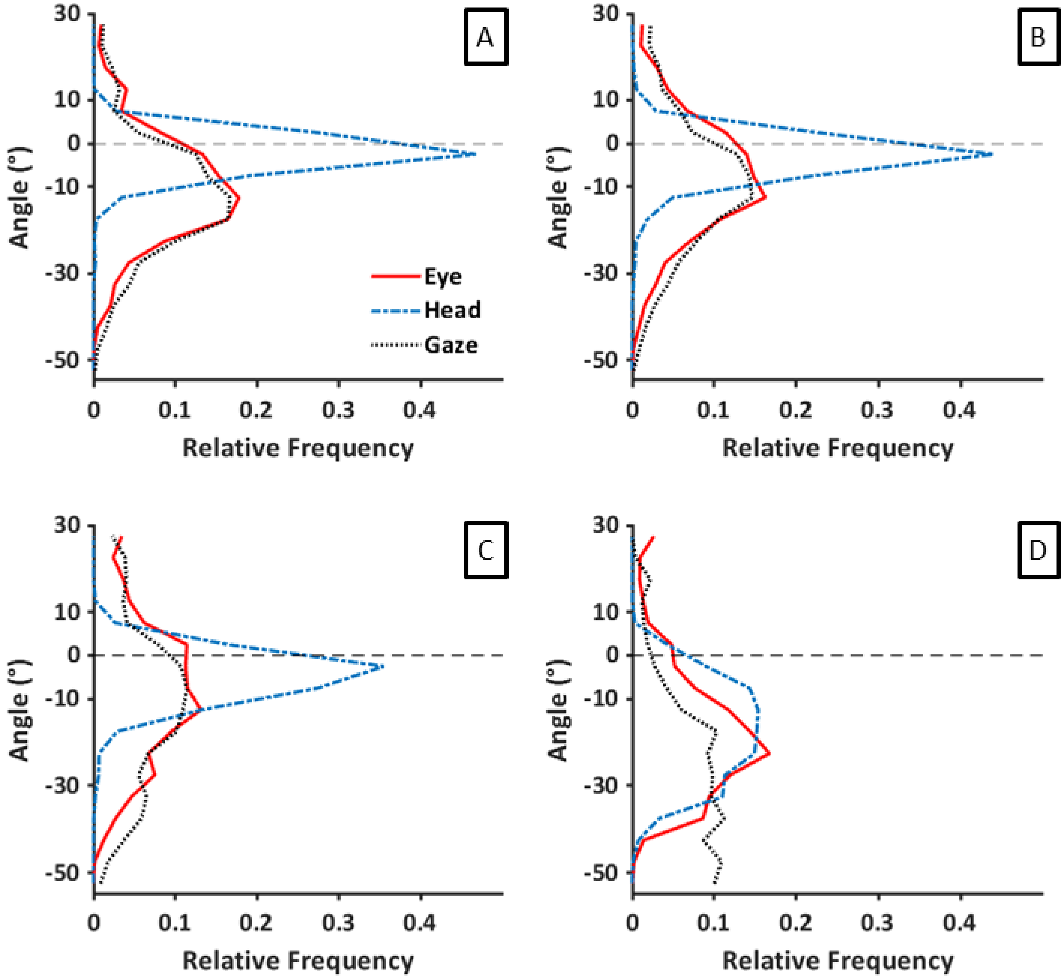

Figure 3: Relative frequency distributions of eye, head pitch and gaze (combined eye and head pitch) angles (°), within a trial for the (**A**) indoor, flat, (**B**) outdoor, paved, (**C**) outdoor, cobbled and (**D**) indoor, uneven surfaces. Negative angles correspond to lowering of the eyes and head toward the ground. An angle of zero (indicated by the black dashed line) represents the mean angle as the participant looked ahead at the start and end of each trial.

2.4.2 Gait speed analyses

Speeds were significantly different across surfaces, $F(3, 30) = 38.40$, $\eta_p^2 = 0.89$ $p<0.001$, as shown in **Figure. 4**. A post-hoc Newman Keuls test ($p < 0.05$) showed participants walked more slowly on the indoor, uneven surface (M ± SE = 1.19 metres/second ± 0.05*)* than the indoor, flat (1.35 ± 0.04), outdoor, paved (1.43 ± 0.04) and outdoor, cobbled (1.44 ± 0.04) surfaces.

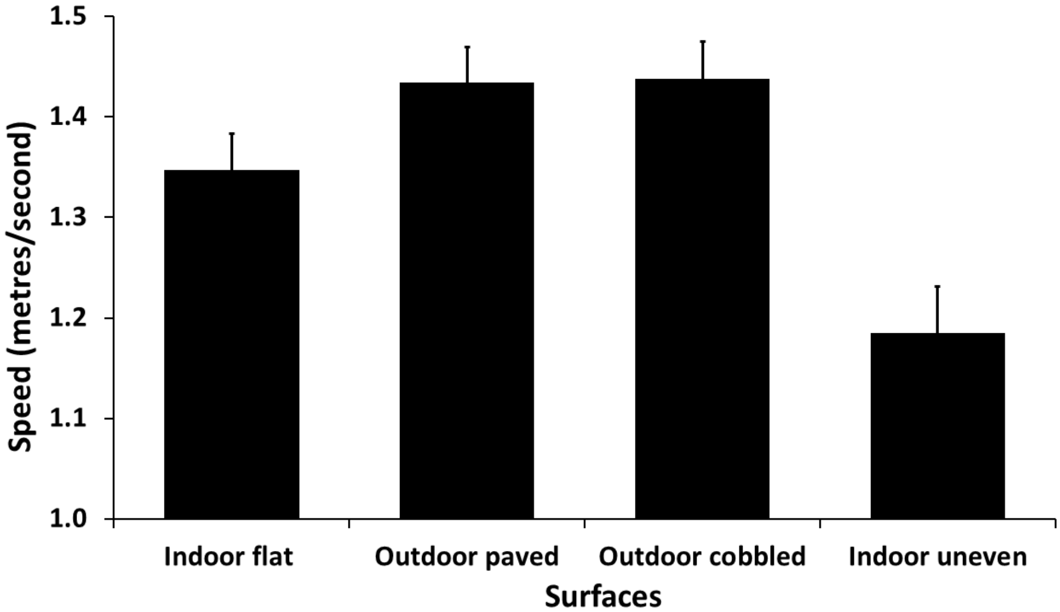

Figure 4: Mean (± SE) gait speed (metres/second) for the four surfaces (indoor, flat, outdoor, paved, outdoor, cobbled and indoor, uneven).

Correlations of speed were calculated between mean speed and mean eye, head pitch and gaze angle over the trial. One sample t-tests revealed that no correlations with speed were significantly different from zero, see **Table 1**.

Table 1*:* Correlations between mean gait speed and mean eye, head pitch and gaze angles (°).

		Indoor, flat	Outdoor, paved	Outdoor, cobbled	Indoor, uneven
Eye angle (°)	Mean (±SD)	+0.01 (±0.29)	-0.14 (±0.37)	-0.04 (±0.39)	+0.09 (±0.28)
	t value	0.08	-1.21	-0.32	1.07
	p value	*0.936*	*0.255*	*0.755*	*0.311*
Head pitch angle (°)	Mean (±SD)	-0.08 (±0.37)	+0.09 (±0.36)	-0.06 (±0.41)	-0.11 (±0.35)
	t value	-0.69	0.83	-0.52	-1.07
	p value	*0.508*	*0.428*	*0.613*	*0.310*
Gaze angle (°)	Mean (±SD)	+0.03 (±0.33)	+0.06 (±0.35)	+0.06 (±0.41)	+0.07 (±0.32)
	t value	0.28	0.54	0.46	0.67
	p value	*0.789*	*0.601*	*0.654*	*0.516*

We estimated how long it would take participants to walk to the location that they were fixating for each surface. To do this, we used the average participant eye height and their mean gaze (combined eye and head pitch) angle to calculate the mean distance that participants were looking ahead for each surface. We then divided this distance by the average participant gait speed for that surface to estimate how long it would take for participants to walk to their fixation location, see **Table 2.** This was shortest for the indoor uneven surface. Similarly, using the average step length for each surface, we calculated how many steps people looked ahead. People looked fewer steps ahead on the indoor uneven surfaces, see **Table 2**.

Table 2: Mean (± SD) time (seconds) and mean number of steps to reach the location that participants were looking ahead to.

	Indoor, flat	Outdoor, paved	Outdoor, cobbled	Indoor, uneven
Look ahead time (sec) *(± SD)*	6.37 *(±0.12)*	7.88 *(±0.12)*	6.82 *(±0.12)*	2.23 *(±0.15)*
Look ahead step number *(± SD)*	6.12 *(±0.22)*	7.75 *(±0.29)*	6.66 *(±0.25)*	2.00 *(±0.07)*

2.5 Discussion

The aim of this exploratory study was to understand how eye angle and head pitch angle contribute to gaze behaviour and how this alters with gait speed when walking over surfaces of different complexity. When traversing the most complex surface (indoor, uneven; mean height change= 7.46°, see **Figure 1**), participants significantly lowered their gaze (combined eye and head pitch) angle and reduced their gait speed. Head pitch angle was lowered towards the ground for a greater duration of the trial over this surface (as shown by the relative frequency distribution, see **Figure 3**), and a greater proportion of gaze angle was attributed to head pitch angle than for any other surface (54%). Our results suggest that more complex surfaces require greater visual information to traverse, with a stronger contribution to overall gaze angle being made by head pitch angle in such circumstances.

The results in our study are consistent with previous research in showing that complex surfaces exert increased visual demands ('t Hart & Einhauser, 2012; Marigold & Patla, 2007; Matthis, et al., 2018) as it becomes harder to maintain stability. Using mean values of gaze (combined eye and head pitch) angle and speed, we showed that participants walking over the indoor, uneven surface looked just two steps ahead (see **Table 1**). This finding is in line with that previously reported when walking on inconsistently spaced foot holds (Matthis, et al., 2017; Matthis & Fajen, 2014). Further research is required to test how different characteristics of irregular surfaces (slope, unevenness, appearance, texture, etc.) influence eye and head pitch behaviour. The present study only measured surfaces by changes in their mean height. An important future goal will be to characterise surfaces using comprehensive, objective and replicable measures.

A relatively novel aspect of the current study was analysing eye and head pitch angle independently when walking over different surfaces. Our results found no strong relation between eye and head pitch angle (note, though, that our analyses could not detect short-term correlations). Only two surfaces (indoor, flat and outdoor, paved) produced a significant correlation between eye and head pitch angles and these correlations were weak. For these simpler surfaces there was some evidence that eye and head movements were co-ordinated. This might reflect participants spending more time gazing around the scene rather than having to fixate near to their upcoming foot placements on these less challenging surfaces. The relative frequency plots (see **Figure 3**) showed differences between eye and head pitch angles. The eyes were typically lowered more than the head except when walking over the most complex indoor, uneven surface. This suggests that the energetically costly movement of the head to shift gaze is only implemented when necessary, i.e. when surfaces are more complex to traverse, compromising stability. This supports findings from 't Hart and Einhauser (2012), showing eye movements are usually greater than head movements. Furthermore, these results strengthens the rationale of Tomasi, et al. (2016) for calculating gaze from *both* eye and head movements. The lack of contribution from the head to overall gaze when walking over smooth surfaces may suggest that our peripheral vision is sufficient in these settings. Indeed, peripheral vision has been shown to be sufficient even when traversing an obstacles (Graci, et al., 2010). Future research is therefore required to determine how complex surfaces must be in order to elicit lowering of the head.

In our study, changes in eye angle, head pitch angle and gait speed were assessed from mean values across the entire length of the surface traversed on a given trial. We found significant differences between surfaces using this approach (see **Figure 2**), and we believe that this summary measure provides a convenient and meaningful summary of gaze behaviour over different surfaces. Surface lengths changed slightly between surfaces, but given that we excluded data from the start and end of the surface, differences of surface complexity are likely to be the main cause of behavioural change.

A more detailed approach to determine gaze behaviour can come from time series data, for example as used by Matthis, et al. (2018). The supplementary material (2.7.4) shows an example of time series data from our study, plotting raw gaze angle for ten trials of one participant walking over the outdoor, cobbled and the indoor, uneven surfaces. For this participant, gaze was consistently lower for the indoor, uneven surface compared to the outdoor, paved surface, whilst overall gaze angles were generally lower.

2.6. Conclusions

In summary, we found gaze and gait behaviour to be most affected when participants walked on a complex, uneven surface. In this situation both head and eye movements played a substantial role in determining gaze angle, supporting the argument (Tomasi, et al., 2016) that we should not assess gaze solely by considering eye movements. This research should act as a foundation for future work to tease apart what surface characteristics drive behavioural changes in gaze and gait when we walk over the types of surfaces that we commonly encounter in our everyday lives (e.g. slopes, cobbles, steps).

2.7 Supplementary material

2.7.1. Eye tracker calibration

Before commencing walking, participants completed an eye calibration. The calibration tracked eye movements whilst the participants remained still at a distance of 320cm from a screen (173cm x 265cm), following recommendations made using the Arrington ViewPoint® manual (Arrington ViewPoint, 2010). The eye height of participants whilst standing was also measured.

2.7.2 Accuracy of inertia measurement unit sensors (IMUs)

Previous research has shown that IMUs can be used to calculate head yaw whilst walking outdoors (Tomasi, et al., 2016). However, the accuracy of IMUs to calculate head movement has not been tested. Furthermore, despite previous research showing IMUs to be accurate at calculating gait speed (Li, et al., 2010), this has not been tested for walking over irregular surfaces. We therefore tested the accuracy of IMU measures of head pitch angle and gait speed for flat and uneven surfaces. To achieve this, we compared data from IMUs to the gold standard assessment of spatiotemporal gait parameters, motion capture cameras (MOCAP).

2.7.2.1 Method

The test involved one individual walking over the two indoor surfaces tested in the study (**Figure 1A** & **1D**). Two IMUs (Delsys TRIGNO™ IM, Boston, MA, USA) were placed on the body, positioned at the midline of the forehead and the lateral left shank. The lateral shank was selected following the methodology described by Li, et al. (2010), and this protocol was used for the gait speed calculation. MOCAP cameras (Qualisys Oqus 7 cameras) were used to record head pitch angle and gait speed using Qualisys Track Manager (version 2.15). Four reflective markers were placed on a headband strapped to the head and four markers were attached to a marker plate, placed at the lumbar region. Head pitch angle was calculated from the average vertical gyroscopic movement at the head and gait speed was calculated from the average acceleration and positional data of the four lumbar markers. .

The participant walked ten times over the indoor, smooth surface and the indoor uneven surface. To check the IMUs accuracy for gait speed calculation, the participant walked at a comfortable walking speed as well as a range between the fastest and slowest possible walking speeds.

2.7.2.2 Accuracy of the IMUs to calculate head pitch angle and gait speed

Both head pitch angle and gait speed correlated highly between the MOCAP and the IMU data (0.98 and 0.89 respectively). For gait speed, the discrepancy between MOCAP and IMU results was greatest when walking fast over uneven surfaces. These speeds were faster than the fastest speeds of participants in the main study. For all other gait speeds, errors were similar to those obtained by Li, et al. (2010).

2.7.3. Validation of eye movement

We completed a validation study of the possible eye movement range in the vertical direction. 10 healthy adults (5 male, mean ± SD; age = 27.4 ± 1.1 years; height = 175 ± 9.2cm) were asked to rate their visual comfort across a range of eye angles (+40° to -70°) on a Likert scale between 1 and 5 (1 = “very fresh” 5 = “severe strain”. This scale was taken from Shibata, Kim, Hoffman, and Banks (2011). Participants were instructed to keep their head still, whilst fixating at targets set incrementally (in steps of 10°) from their eye height (defined as 0°). Only eye movements between +30° and -50° were, on average, rated at a comfort rating of 4 (moderate strain) or below. Any recorded eye movements outside of this range were excluded from the analysis because participants were deemed unlikely to move their eyes to cause them severe strain.

2.7.4. Examples of time series data

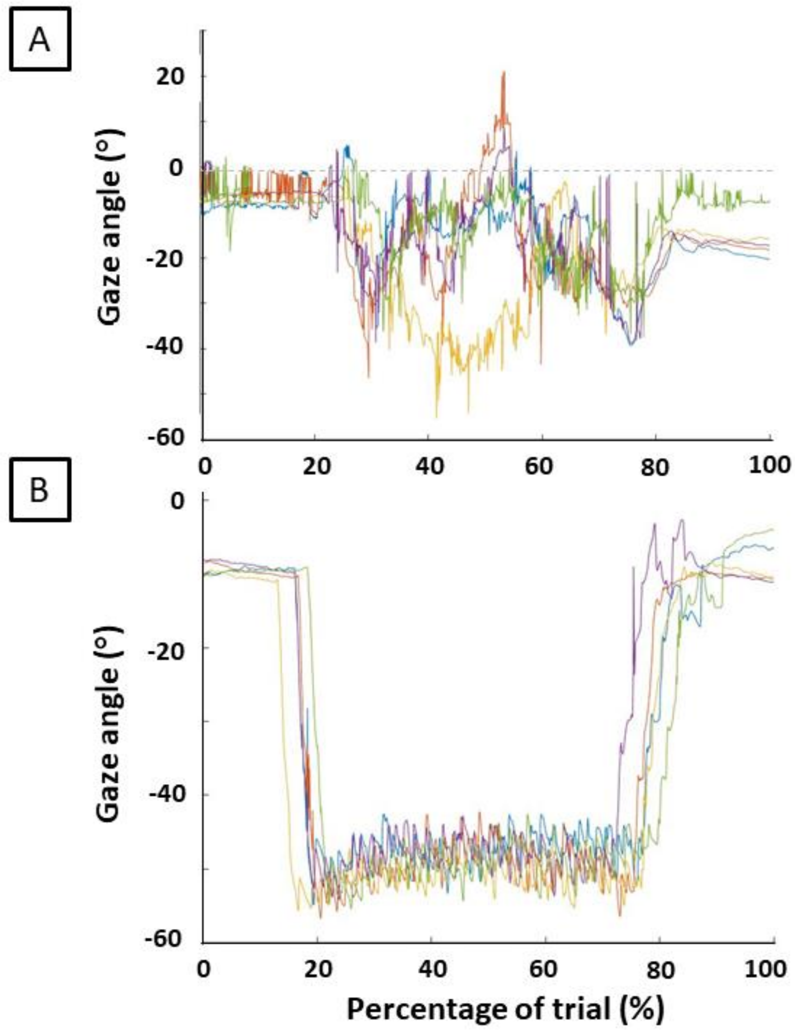

Figure 2.7.4: Sample gaze (combined eye and head pitch) angles (°) over the course of ten individual trials for one participant walking over the (**A**) outdoor, cobbled surface and (**B**) indoor, uneven surface. Different colours represent each of the ten trials in each of these two conditions.

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

In establishing that surface complexity is an important factor to determine gaze and gait speed behaviour (Chapter 2), I now need to establish a more objective measure for surface complexity. Previous research has predominately used descriptions to characterise different surfaces. The aim in this chapter was to develop a multimethod approach to more objectively define different surfaces. Two different forms of surface measures (physical and perceptual measures) were used to assess surface complexity. Firstly, I compared a number of physical and perceptual measures to one another, and secondly, determined whether these measures were indicative of changes to stability as assessed from a range of gaze and gait behaviours. In doing so, multiple surface types can be compared and certain conditions can be identified as more complex. Moreover, this approach may lead to a potential simple and easy measure for surface complexity using surface perception measurements.

This chapter has been published as:

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The primary author conceived and designed the experiments, conducted the experiments, analysed the data, prepared the figures and tables, authored and approved the final draft.

We have also added additional analyses not included in the published manuscript, see Additional materials.

3.1 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**.**

3.2 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 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, assessing several behavioural measures simultaneously 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 ('t Hart & Einhauser, 2012; Marigold & Patla, 2007; Matthis, Yates, & Hayhoe, 2018; Thomas, Gardiner, Crompton, & Lawson, 2020b). 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 timeconsuming 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, 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.

3.3 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 **Figure 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 10m long to ensure that participants walked far enough to achieve a steady state of walking (Najafi, Miller, Jarrett, & Wrobel, 2010).

Figure 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.

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

3.3.1 Physical measurements

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 $1m^2$ (2m along the direction of walking x 0.5m 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 x 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 software. Once created, we used Meshlab software (Cignoni, et al., 2008) to simplify each model to 20,000 triangular faces.

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 metre x 0.5 metre 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**.

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

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.

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 toward 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 (3.7.1).

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, 12cm long extent placed onto the surface. This was done at 20 locations along each surface, with each location separated by approximately 30cm.

3.3.2 Perception measurements

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 ± 8.5cm. Twelve of these participants (10 male, age = 27.3 ± 4.3 years; height = 178.0 ± 6.9cm) 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, ($F(1, 32) = 0.22$, $\eta_p^2=0.01$, $p=0.643$) so responses were pooled in the analyses reported here.

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.

3.3.3 Behavioural measurements

Participants

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

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 30Hz and a world view at 60Hz. 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 148Hz. 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). We determined the accuracy of this algorithm to detect symmetrical data (see Additional Material). Two sensors were positioned above the malleoli on each leg 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 **Figure 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, 2020a) 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, $F(1, 18) = 0.38$, $\eta_p^2=0.02$, $p=0.544$. 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.

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. (2020b). Head pitch angles were calculated using the gyroscopic data from the forehead sensor. The gyroscopic data were filtered using a low pass, 10Hz 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 walking[1]. 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.

3.4 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 (3.7.2).

3.4.1. 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**.

Table 3: Correlations between the mean z-scores for all 17 surfaces for every pair of physical and perceptual measures. 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 < 0.003 (*calculated using the Bonferroni adjustment).

	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***

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**.

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. 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 $p < 0.003$ (calculated using the Bonferroni adjustment).

	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***

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 component analysis (PCA). Two components were established based on a criterion of the component accounting for at least 10% of the variance, see **Figure 2**.

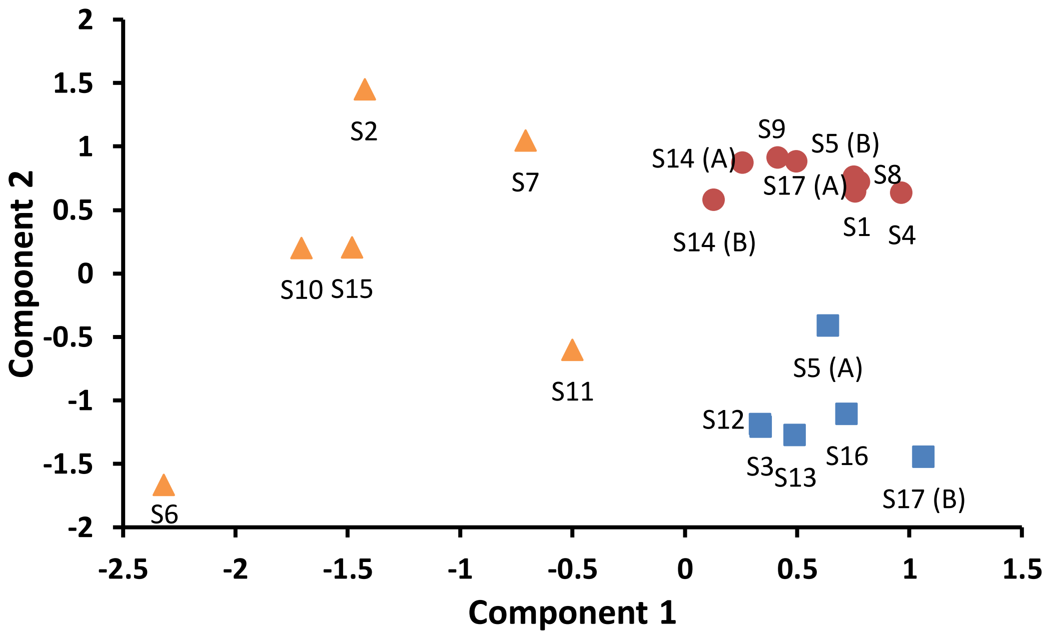

Figure 2: A plot of the first two components of the PCA including the three physical and three perceptual measures. Component 1 (variance = 66.4%) consisted of the roughness rating, pre-walk stability rating, post-walk stability rating, mean local slope angle and DNE. Component 2 (variance = 21.3%) consisted 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.

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 (3.7.3). These three groups of surfaces will henceforth be described as smooth (red circles), stairs (blue squares) and uneven (orange triangles).

3.4.2 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 (3.7.4).

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 participants that completed both the behaviour and perception task. Correlations were lower, but showed a similar pattern, see the supplementary material (3.7.5).

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. Bold values represent large effect sizes (abs(r) > 0.5), as determined by Cohen (2013). * signifies $p < 0.005$ (calculated using the Bonferroni adjustment).

	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**

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 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.

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. Bold values represent large effect sizes (abs(r) > 0.5), as determined by Cohen (2013). * signifies $p < 0.0017$ (calculated using the Bonferroni adjustment).

	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**

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. Bold values represent large effect sizes (abs(r) > 0.5), as determined by Cohen (2013). * signifies $p < 0.0017$ (calculated using the Bonferroni adjustment).

	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***

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 **Figure 3**.

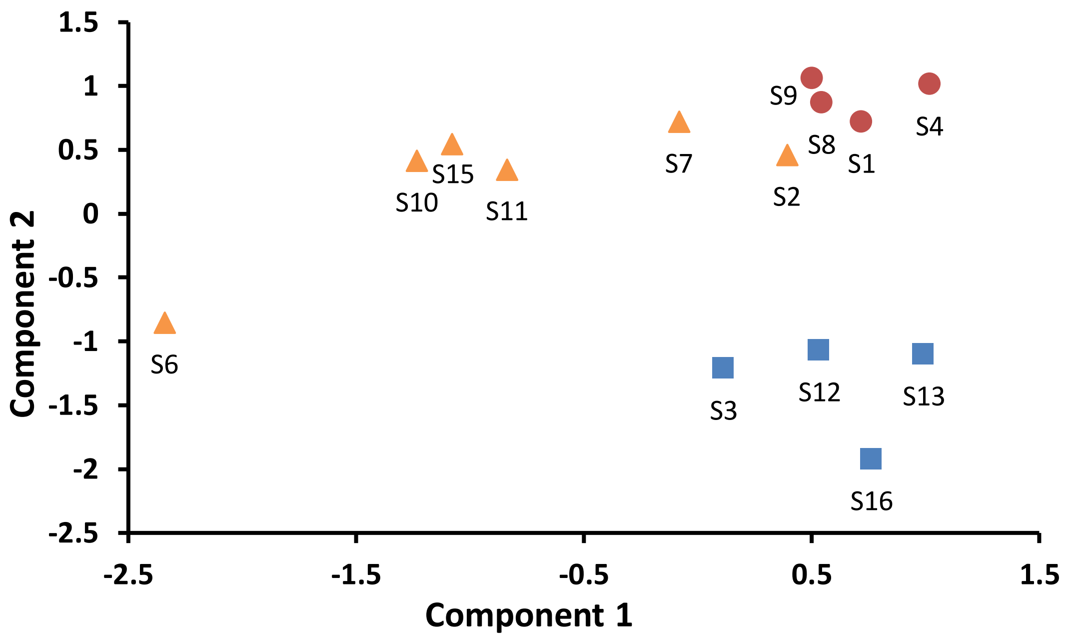

Figure 3: A plot of the first two components of a Principal Component Analysis (PCA) between the 5 behavioural, 3 perceptual and 3 physical measurements. Surfaces are coloured based on the three groups established in **Figure 2**. Component 1 (variance = 55.3%) consisted of mean local slope angle, DNE, 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.

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 **Figure 4.**

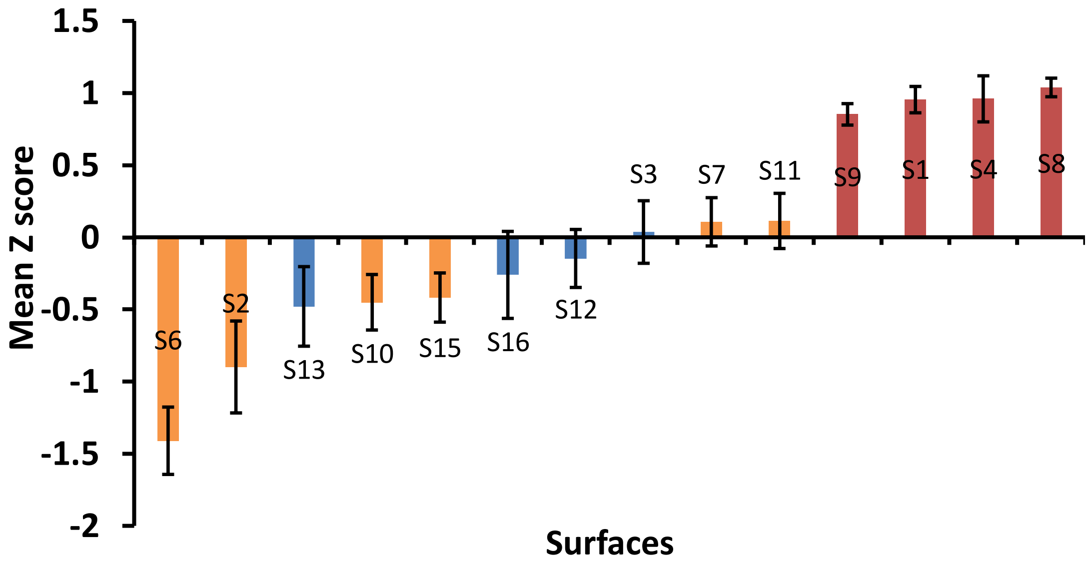

Figure 4: Ranked mean (± SE) z-scores for each of the 14 single part surfaces across all the 11 measures. Lower z-scores are indicative of more difficult surfaces, i.e. more complex and less stable for walking over. Surfaces are coloured according to the same smooth (red), stairs (blue) and uneven (orange) groups used in **Figures 2** and **3**.

3.5 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 **Figure 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 using 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 **Figure 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 (**Table 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., 2020b). 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., 2020a).

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 (**Figure 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.

3.6 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.

3.7 Supplementary material

3.7.1 Dirichlet Normal Energy (DNE) bandwidth

Methodology of ariaDNE bandwidth selection to calculate DNE

To assess the features influencing walking on surfaces, we needed to consider which bandwidth would be most appropriate for the ariaDNE calculation of DNE. The bandwidth of the model is changed through the parameter ε in the Gaussian kernel function ($f(X) = e^{-x^2/\varepsilon^2}$). Here, we compared how ε affected the DNE for models of three different surfaces (S1, flagstone paving; S3, concrete stairs; and S6, loose stones).

DNE results dependent on the weight selection for the ariaDNE calculation

The DNE values based on different weights of ε are shown in **Figure 3.7.1.1**. S1 was a smooth surface so the DNE values were much smaller than that of S3 and S6, and were not clearly visible on this graph.

Of the remaining two surfaces, using a larger bandwidth included a larger localised area, which, for S3, meant that changes in stair level were considered in the measure. This is not what we aimed to assess with DNE, given that we wanted to look at surface features that affect our walking, i.e. those features affecting stability underfoot. **Figure 3.7.1.2** illustrates what features influenced the DNE calculation at different bandwidths.

Increased bandwidth values of ε for S6 removed some of the localised changes (i.e. between stones). The S3 surface showed that localised changes were overshadowed by changes in stair height at higher bandwidth which was not relevant for our purposes given that a foot cannot stand on two different steps at once. We therefore chose a low bandwidth of 0.02 in our calculation of DNE in our study.

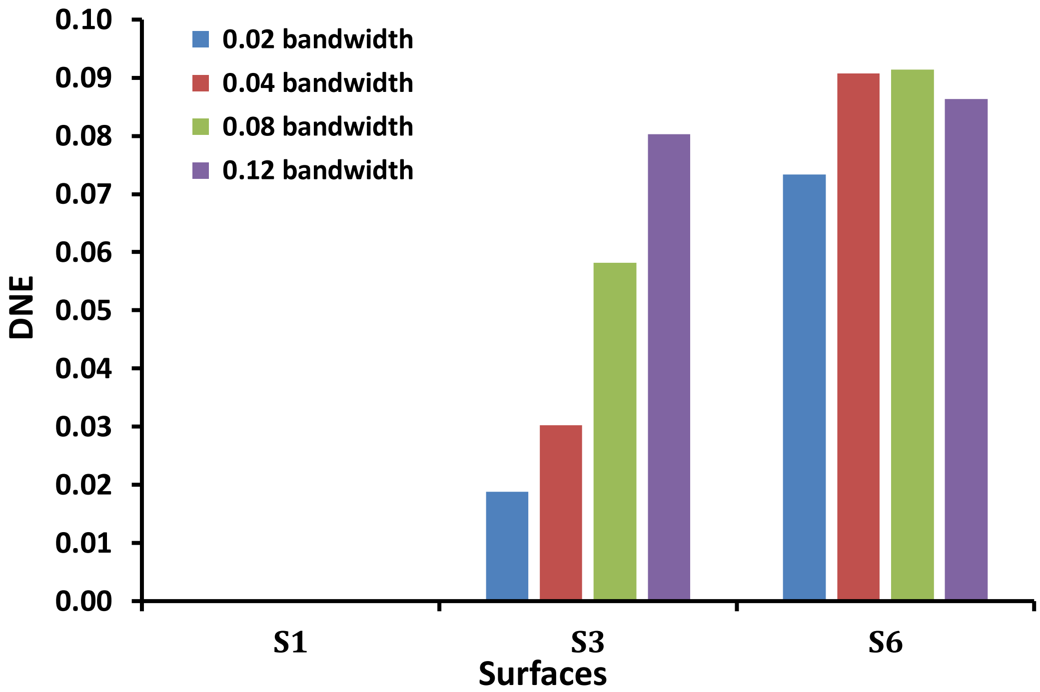

Figure 3.7.1.1: DNE values calculated at bandwidths of ε = 0.02, 0.04, 0.08 and 0.12 for three surfaces (S1, flagstone paving; S3, concrete stairs; and S6, loose stones).

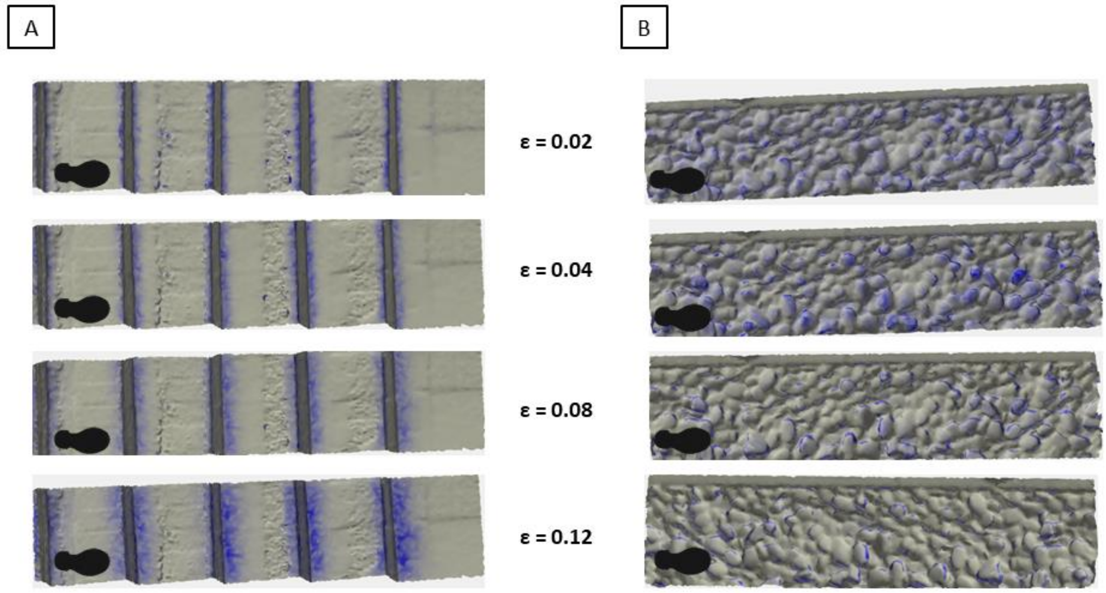

Figure 3.7.1.2: Plotted energy values (blue areas) at different bandwidths (ε) for surfaces **(A)** S3 (concrete stairs) and **(B)** S6 (loose stones). An outline of a foot (UK male size = 10) is shown for scale for each model

3.7.2 Mean values (±SE) for all eleven of our measures across surfaces (S1 – S17).

Table 3.7.2: Mean values (±*SE*) for each of the 3 physical, 3 perceptual and 5 behavioural measures calculated for each of the 17 surfaces (S1 – S17). For the perception measures, surface roughness was rated from 1 = "completely smooth" to 10 = "extremely rough" and stability was rated from 1 = "no problem with stability" to 10 = "I think I might fall over" if they were to walk on the surface.

	Physical measures			Perception measures			Behaviour measures				
Surfaces	Relief index	DNE (x1000)	Mean local slope angle (°)	Roughness rating	Pre-walk stability rating	Post-walk stability rating	Eye angle (°)	Head angle (°)	Gait speed (m/s)	Harmonic ratio	Muscle coactivation (%)
S1	1.027	0.18	0.47	2.2	1.6	1.3	-17.07	-3.12	1.36	3.95	13.93
			(0.11)	*(0.16)*	*(0.13)*	*(0.11)*	*(2.17)*	*(1.09)*	*(0.04)*	*(0.31)*	*(0.89)*
S2	1.039	4.79	2.05	6.2	7.3	6.6	-23.65	-17.11	1.06	1.86	16.85
			(0.49)	*(0.22)*	*(0.21)*	*(0.30)*	*(3.62)*	*(3.31)*	*(0.03)*	*(0.18)*	*(1.39)*
S3	1.309	18.86	0.92	3.8	2.9	2.4	-16.70	-9.96	0.93	2.13	13.59
			(0.22)	*(0.19)*	*(0.22)*	*(0.23)*	*(2.95)*	*(1.24)*	*(0.05)*	*(0.17)*	*(1.08)*
S4	1.010	0.15	0.74	1.4	1.1	1.3	-20.20	-3.51	1.47	3.76	13.00

			(0.12)	*(0.11)*	*(0.06)*	*(0.11)*	*(2.90)*	*(0.87)*	*(0.03)*	*(0.27)*	*(0.97)*
S5A	1.193	7.55	1.00	2.6	2.3	1.9	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
			(0.16)	*(0.13)*	*(0.16)*	*(0.19)*					
S5B	1.008	0.17	0.47	-	-	-	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
			(0.15)								
S6	1.306	73.35	10.45	7.1	5.8	6.3	-19.01	-19.27	1.09	1.87	17.05
			(2.05)	*(0.28)*	*(0.28)*	*(0.31)*	*(2.28)*	*(1.92)*	*(0.04)*	*(0.13)*	*(0.99)*
S7	1.040	5.01	2.74	5.3	4.4	3.8	-18.56	-12.04	1.30	2.78	13.25
			(0.56)	*(0.27)*	*(0.27)*	*(0.32)*	*(3.49)*	*(1.84)*	*(0.06)*	*(0.18)*	*(1.16)*
S8	1.010	0.62	0.53	2.0	1.6	1.7	-16.13	-4.86	1.50	3.89	13.26
			(0.09)	*(0.11)*	*(0.18)*	*(0.19)*	*(1.81)*	*(1.26)*	*(0.03)*	*(0.23)*	*(0.96)*
S9	1.003	0.79	0.71	3.1	2.1	1.8	-17.59	-5.43	1.51	3.81	13.76
			(0.11)	*(0.22)*	*(0.24)*	*(0.17)*	*(2.11)*	*(0.56)*	*(0.03)*	*(0.21)*	*(1.06)*
S10	1.115	30.95	8.53	6.4	4.9	4.8	-18.89	-8.67	1.19	2.60	14.95
			(1.30)	*(0.29)*	*(0.28)*	*(0.32)*	*(2.36)*	*(1.43)*	*(0.07)*	*(0.14)*	*(1.15)*

S11	1.142	38.62	6.58	3.5	2.7	2.5	-18.93	-6.33	1.47	2.66	14.07
			(0.95)	*(0.20)*	*(0.23)*	*(0.21)*	*(2.82)*	*(1.01)*	*(0.04)*	*(0.14)*	*(1.18)*
S12	1.332	14.85	0.68	4.0	3.1	2.6	-20.27	-8.98	0.92	2.00	13.95
			(0.10)	*(0.29)*	*(0.27)*	*(0.23)*	*(2.59)*	*(1.08)*	*(0.06)*	*(0.13)*	*(1.20)*
S13	1.332	14.85	0.68	3.4	3.0	2.5	-23.48	-12.41	0.94	2.17	17.41
			(0.10)	*(0.24)*	*(0.22)*	*(0.22)*	*(1.72)*	*(1.01)*	*(0.05)*	*(0.14)*	*(1.20)*
S14A	1.022	0.23	1.21	3.4	2.4	2.3	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
			(0.21)	*(0.20)*	*(0.27)*	*(0.20)*					
S14B	1.042	8.64	2.11	-	-	-	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
			(0.42)								
S15	1.097	34.79	6.37	6.0	5.0	4.6	-19.40	-11.99	1.40	2.41	15.20
			(1.02)	*(0.24)*	*(0.31)*	*(0.28)*	*(3.19)*	*(1.51)*	*(0.04)*	*(0.12)*	*(1.09)*
S16	1.303	10.65	0.58	2.4	2.9	2.6	-17.54	-14.55	0.59	1.91	16.24
			(0.12)	*(0.25)*	*(0.24)*	*(0.22)*	*(2.86)*	*(1.69)*	*(0.03)*	*(0.13)*	*(1.20)*
S17A	1.007	0.16	0.53	2.1	1.6	1.7	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*

			(0.09)	*(0.19)*	*(0.12)*	*(0.13)*					
S17B	1.323	12.68	0.68	-	-	-	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
			(0.15)								

NB. S12 and S13 are the same surface (stairs) but ascending and descending respectively, thus physical measures are the same. As the relief index and DNE values are computed from a single 3D model, no standard error values are given. Only one perceptual measure is shown for surfaces with two components (S5, S14, and S17), since participants were asked to consider both parts and give an overall rating. Surfaces with two components did not have behavioural measures calculated and therefore no data (N/A) is reported.

3.7.3 The most common verbal descriptions for each of the three groups of surfaces.

Table 3.7.3: The count of the five most common verbal descriptions provided by participants for each of the three groups of surfaces

Most common descriptions	Red group		Blue group		Orange group	
1	Smooth	44	Pebbles	43	Stairs	70
2	Paving	38	Uneven	35	Steps	40
3	Gravel	36	Stones	29	Smooth	18
4	Flat	34	Sloped	26	Steep	16
5	Grass	27	Grass	25	Paving	12
Total words provided		329		399		253

NB: Total words shows the overall number of words given by all participants for each group of surfaces.

3.7.4 Rationale for removing the three surfaces with two distinct components

For our study, behavioural changes were assessed from mean values across the surface length. Although surfaces length did differ between surfaces, as we assessed mean values and most data was not collected from walking over the start or end of each surface, differences of surface complexity are likely to be the main cause of behavioural changes. Due to using mean values, surfaces with two distinct components (S5, S14 and S17) were excluded from this part of the analysis. This is due to previous studies having shown that a transition between different surfaces changed gaze and gait behaviour (Chang, Chang, Lesch, & Matz, 2017; Miyasike-DaSilva, et al., 2011; Miyasike-daSilva & McIlroy, 2012). Behaviour for these surfaces would have to be assessed over time. This has recently been demonstrated for gaze behaviour over complex surfaces by Matthis, et al. (2018).

3.7.5 Mean correlations between every pair of perceptual and behavioural measures for the 12 individuals that completed both studies.

Means of the twelve correlations between the mean z-scores for the 14 surfaces (excluding the three surfaces with two components) for every pair of perceptual and behavioural measures. Each of the twelve individuals that completed both the perception and the behavioural tasks contributed one set of correlations to this mean. All these mean correlations were significantly different from zero ($p < 0.01$), as determined by t-tests.

Table 3.7.5: Mean correlations between perceptual and behavioural measures

	Pre-walk stability rating	Post-walk stability rating	Eye angle	Head angle	Gait speed	Harmonic ratio	Muscle coactivation
Roughness rating	0.78	0.76	0.17	0.49	0.17	0.43	0.22
Pre-walk stability rating	-	0.86	0.31	0.59	0.18	0.58	0.24
Post-walk stability rating	-	-	0.28	0.58	0.33	0.50	0.29
Eye angle	-	-	-	0.28	0.20	0.20	0.18
Head angle	-	-	-	-	0.20	0.65	0.43
Gait speed	-	-	-	-	-	0.64	0.27
Harmonic ratio	-	-	-	-	-	-	0.37

Footnote

[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

Additional material

Please note that this section contains details not included in the published paper

Harmonic Ratio algorithm accuracy

Harmonic ratios of a stride have previously been described as a good measure of walking smoothness (Bellanca, et al., 2013; Gage, 1964; Menz, et al., 2003). However, we needed to ensure the accuracy and suitability of this measure for the current study. The harmonic ratio algorithm, used in this study, was written in MATLAB (v R2018B) code, using the fast Fourier transform functions. The first ten odd and first ten even harmonic coefficients were used in the calculation of harmonic ratio. This method has been used by others when analysing accelerometric walking data (Bellanca, et al., 2013; Smidt, et al., 1971).

Methodology

To test the algorithm, we completed two tests. Firstly, to ensure that the algorithm was accurately calculating harmonic ratios, we produced artificial data of known harmonic ratios to then test our algorithm (**Test A**). The artificial data was created within MATLAB using values from a random number generator (a, phi) and inputted into the following equation:

$$s_N(x) = \frac{A_0}{2} + \sum_{n=1}^{N} A_n \cdot \sin\left(\tfrac{2\pi n x}{P} + \phi_n\right), \quad \text{for integer } N \geq 1.$$

This was done for an N value of 10 at a sampling rate of 50Hz for x values that are factors of pi.

Secondly, to ensure that the algorithm worked on accelerometric data when walking, we compared normal walking to that when walking with an asymmetric gait (**Test B**). An asymmetric gait was achieved by a walk that consisted of one step being smaller than the other (limping). As the harmonic ratio measures walking smoothness by the symmetry of gait, walking with a limp should produce smaller harmonic coefficients. One participant (male, age = 25, height = 176cm, weight = 67kg) completed five walking trials for each walking type (normal and limping), on a smooth wooden surface see indoor surface in (Thomas, et al., 2020b) for details. Accelerometric data was collected from a singular IMU placed at the pelvis.

Results

Test A showed that the algorithm was accurate based on the artificial data showing over 98% accuracy. The small differences are likely due to the noise purposely added to the artificial data. We can therefore be very confident that algorithm is accurately measuring harmonics ratios. **Test B** showed that a lower harmonic ratio was found for all three directions of accelerometric data when walking with a limp, see **Figure AM**. Therefore, we can be confident that the created harmonic ratio algorithm was used accurately to detect walking symmetry.

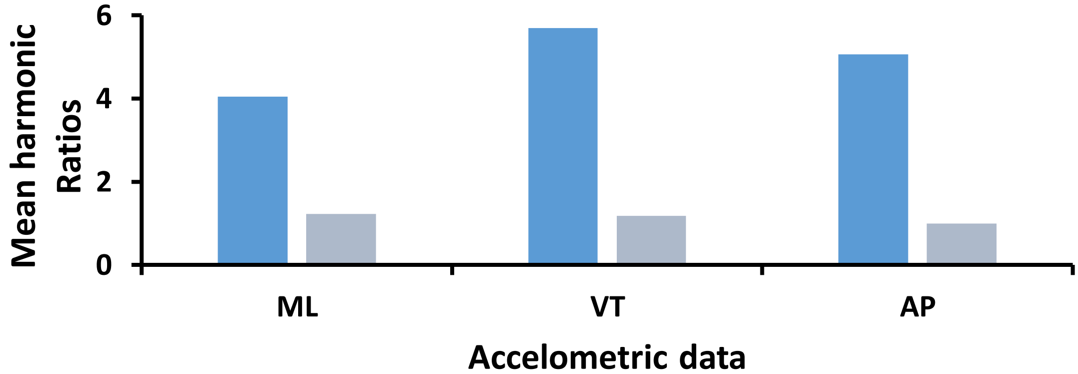

Figure AM: Mean harmonic ratios produced for the mediolateral (ML), vertical (VL) and anteroposterior (AP) accelerometric data for a normal (blue) and limping (grey) gait.

3.8 References

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Chapter Four: Maintaining gait stability in challenging conditions

I have now shown that a number of behavioural changes, indicative of stability, occur when the surface complexity is increased, and that both physical and perceptual measures of the surfaces are a good, objective proxy for these changes (Chapter 3). Whilst more complex surfaces are a common extrinsic cause for a fall, it is also important to determine how intrinsic factors affect stability. In particular, lower visual field loss has been shown to be important for stability with age (Black, Wood, & Lovie-Kitchin, 2011), whilst simulations of lower visual field loss have proven to elicit similar behaviours to those with age-associated vision loss (Krishnan, Cho, & Mohamed, 2017). The aim in this chapter was to assess the impact of simulated lower visual filed loss when walking over a range of surfaces outside. Using perceptual measures as a metric for surface complexity, gaze and gait behaviour was assessed for participants that walked with and without a blocked lower visual field. In simulating one intrinsic factor, associated with heightened fall risk, the importance of the lower visual field for stability whilst walking, and whether this changes dependent on the environment, can be assessed

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The primary author conceived and designed the experiments, conducted the experiments, analysed the data, prepared the figures and tables, authored and approved the final draft.

4.1 Abstract

Background: Peripheral vision often deteriorates with age, disrupting our ability to maintain normal locomotion. Laboratory-based studies have shown that lower visual field loss, in particular, is associated with changes in gaze and gait behaviour whilst walking and this, in turn, increases the risk of falling in the elderly. Separately, gaze and gait behaviours change and fall risk increases when walking over complex surfaces. It seems probable, but has not yet been established, that these challenges to stability interact.

Research Question: How does loss of the lower visual field affect gaze and gait behaviour whilst walking on a variety of complex surfaces outside of the laboratory? Specifically, is there a synergistic interaction between the effects on behaviour of blocking the lower visual field and increased surface complexity?

Methods: We compared how full vision versus simulated lower visual field loss affected a diverse range of behavioural measures (head pitch angle, eye angle, muscle coactivation, gait speed and walking smoothness as measured by harmonic ratios) in young participants. Participants walked over a range of surfaces of different complexity, including pavements, grass, steps and pebbles.

Results: In both full vision and blocked lower visual field conditions, surface complexity influenced gaze and gait behaviour. For example, more complex surfaces were shown to be associated with lowered head pitch angles, increased leg muscle coactivation, reduced gait speed and decreased walking smoothness. Relative to full vision, blocking the lower visual field caused a lowering of head pitch, especially for more complex surfaces. However, crucially, muscle coactivation, gait speed and walking smoothness did not show a significant change between full vision and blocked

lower visual field conditions. Finally, head pitch angle, muscle coactivation, gait speed and walking smoothness were all correlated highly with each other.

Significance: Our study showed that blocking the lower visual field did not significantly change muscle coactivation, gait speed or walking smoothness. This suggests that young people cope well when walking with a blocked lower visual field, making minimal behavioural changes. Surface complexity had a greater effect on gaze and gait behaviour than blocking the lower visual field. Finally, head pitch angle was the only measure that showed a significant synergistic interaction between surface complexity and blocking the lower visual field. Together our results indicate that, first, a range of changes occur across the body when people walk over more complex surfaces and, second, that a relatively simple behavioural change (to gaze) suffices to maintain normal gait when the lower visual field is blocked, even in more challenging environments. Future research should assess whether young people cope as effectively when several impairments are simulated, representative of the comorbidities found with age.

4.2 Introduction

Maintenance of our stability when walking depends heavily on processing visual information from the environment. Visual information is particularly important for stability when the environment is more complex, leading to people modifying locomotion in real-time for safe navigation (Marigold & Patla, 2007; Matthis, Barton, & Fajen, 2017; Matthis, Yates, & Hayhoe, 2018; Patla & Greig, 2006). We can assess how different environments (and other factors) affect stability by measuring gaze and gait behaviour. Although no stability measure has been accepted as a gold standard (as reviewed in Bruijn, Meijer, Beek, & Van Dieën, 2013), assessing a range of gaze and gait behavioural changes allows the researcher to build up a portfolio of how the body adapts to a given manipulation, such as increasing surface complexity, providing converging evidence about its effect on stability when walking. Such changes may include "dangerous" behaviours that increase fall risk as well as "cautious" behaviours that occur to try to reduce fall risk. For example, when the perceived risk of a fall increases, people have been found to adopt a more cautious gait, characterised by a slower gait with shorter and wider steps (Pirker & Katzenschlager, 2017). Unfortunately, some of these cautious behavioural changes that are intended to reduce fall risk may be dangerous in that they can lead to increased fall risk. For example, increased leg muscle coactivation (simultaneous contraction of an agonist and antagonist muscle) helps to stabilise the leg when walking (Thompson, Plummer, & Franz, 2018). However, a stiff leg is less flexible and therefore has a reduced range of motion which, in itself, is a known risk factor for falls (Chiacchiero, Dresely, Silva, DeLosReyes, & Vorik, 2010; Reddy & Alahmari, 2016). Regardless of whether the behavioural response is intentional, these behavioural changes indicate deviations from normal, stable gait, and thus can help to identify the factors that influence stability and perceived fall risk in a given situation.

When people walk over more complex surfaces several different behavioural changes occur. Here we define complex surfaces as any non-smooth surface including slope changes, uneven surfaces, stairs and inconsistently spaced foot targets (Thomas, Gardiner, Crompton, & Lawson, 2020a, 2020b). Compared to smooth, level walking, complex surfaces are associated with reduced step length, increased step width variability, increased leg muscle coactivation and reduced gait speed (Marigold & Patla, 2008a; Menant, Steele, Menz, Munro, & Lord, 2009; Thomas, et al., 2020a; Voloshina, Kuo, Daley, & Ferris, 2013). Walking on stairs compared to smooth surfaces is associated with increased anteroposterior sway at the lower back and increased step variability (Wang, et al., 2017; Wang, et al., 2014). Gaze (combined eye and head movements) alters when walking over more complex surfaces, with increased fixations and gaze directed closer towards the person's feet ('t Hart & Einhauser, 2012; Marigold & Patla, 2007; Matthis, et al., 2018; Thomas, et al., 2020a). We have developed a multimethod approach to measure surface complexity in order to try to characterise surfaces in terms of behaviour indicative of stability for walking (Thomas, et al., 2020b). We assessed how physical and perceptual measures of surface complexity across a wide range of surfaces influenced gait and gaze. Using these measures, we found that head pitch lowered, muscle coactivation increased and walking symmetry reduced when walking over more complex surfaces.

In young healthy individuals, environmental information can be obtained from peripheral vision (vision outside the centre of gaze fixation). For example, young, healthy individuals can walk over unexpected objects even when they are fixating well above the ground plane such that the obstacles are only visible in the periphery of their lower visual field (Franchak & Adolph, 2010; Marigold & Patla, 2007). However, as people age, both the rate of comorbidities associated with vision loss increase and healthy peripheral vision is known to deteriorate (Beurskens & Bock, 2012; Collins, Brown, & Bowman, 1989; Crassini, Brown, & Bowman, 1988). Given the loss of peripheral vision, visual perception may be disrupted, thus increasing the challenges to the elderly in maintaining stable locomotion, especially over more complex surfaces. For example, lower visual field loss is a symptom of glaucoma, an eye condition that is particularly common in the elderly. Lower visual field loss due to glaucoma is associated with an increased rate of falls (Black, et al., 2011) and people with glaucoma exhibit increased step to step variability in step length, make more erroneous steps, have a slower gait, and fixate closer to their feet (Friedman, Freeman, Munoz, Jampel, & West, 2007; Lajoie, Miller, Strath, Neima, & Marigold, 2018; Mihailovic, et al., 2017; Miller, Lajoie, Strath, Neima, & Marigold, 2018). Another eye condition associated with lower visual field loss, retinitis pigmentosa, results in individuals fixating at the ground for longer when level walking compared to those with normal vision (Timmis, et al., 2017). Studies conducted outside have shown that those with peripheral visual field loss from glaucoma or retinitis pigmentosa make more errors when judging gaps in traffic at pedestrianised crossings compared to those with normal vision (Cheong, Geruschat, & Congdon, 2008). In contrast, eye diseases associated with central visual field loss (e.g. macular degeneration) appear to have less effect on gait, with only a reduction in speed shown when negotiating a curb compared to those with normal vision (Alexander, et al., 2014).

A complicating factor in interpreting these results is that many of these eye diseases are more prevalent with age, and thus study participants are typically older and are likely to have other perceptual, cognitive and musculoskeletal deficits. One alternative, to assessing peripheral visual field loss is to simulate its loss in young individuals who do not suffer from these confounding factors. For young individuals, simulation of lower visual field loss by wearing goggles with the lower area blocked, has been shown to lead to the adoption of a more cautious, slower gait and reduced foot placement accuracy (Graci, Elliott, & Buckley, 2010; Marigold & Patla, 2008b; Rietdyk & Drifmeyer, 2009), all of which are suggestive of a less stable gait. This use of goggles to simulate lower visual field loss, due to eye disease and ageing, has the advantage of being a relatively easy manipulation, however, goggles do not have an identical effect to the eye diseases experienced commonly in the elderly. This is due to the fact that the goggles move with the head, not the eyes, and thus they block a variable amount of the lower visual field. In contrast lower visual field loss due to eye disease blocks information from a constant area of the visual field. Nevertheless, importantly, lower visual field loss from either wearing goggles or eye diseases will typically lead to less information being available from the lower portions of the scene and, in particular, the area around the feet, unless compensatory movements are made, including tilting the head downwards.

In summary, there is undoubtedly a lack of understanding about how peripheral visual field loss affects behaviour whilst walking. Loss of the lower visual field, in particular, appears to increase fall risk whilst walking (Black, et al., 2011; Graci, et al., 2010; Marigold & Patla, 2008b; Rietdyk & Drifmeyer, 2009). However, it remains unclear how the lower visual field influences walking over surfaces representative of those typically encountered outside of the gait laboratory. Here we investigate how combining a simulated lower visual field loss with walking over more complex surfaces changes gaze and gait behaviour. This is critical given that populations who are most vulnerable to falling, such as the elderly, often suffer from multiple challenges simultaneously. These challenges are both intrinsic, due to deteriorating perception, cognition or musculoskeletal function, and extrinsic, due to testing everyday situations such as uneven or slippery surfaces, poor lighting and crowded, fast-changing environments. To isolate the effects of visual field loss and surface complexity on walking behaviour, in the present study, we tested young, healthy individuals who were not suffering from comorbidities. Young people walked over a wide variety of outside surfaces with full vision and whilst wearing goggles which blocked their lower visual field. The surfaces included those that have previously been categorised as smooth, irregular and stairs (Thomas, et al., 2020b). We measured gaze behaviour (head pitch angle, eye angle) and gait behaviour (muscle coactivation, gait speed and walking smoothness as measured by harmonic ratios). We determined how these measures responded to a perceptual measure of surface complexity (see Thomas, et al., 2020b). In combination, these gaze and gait measures allowed us to investigate how people respond when challenged by walking over diverse surfaces when the lower visual field is blocked.

4.3 Methodology

4.3.1 Participants

Twenty healthy adults (13 male, mean ± SD; age = 26.42 ± 4.27 years; height = 176.1 ± 9.33cm) were recruited for the study. No participant had any known impairment or injury which might affect their gait or vision. All the inertia data that was used to identify gait behaviours did not record properly for one participant, so that gait data was only analysed in 19 participants. Furthermore, the inertia data that was collected at the lower back (used to calculate harmonic ratios to provide a measure of walking smoothness) did not record properly for two further participants, and for one of those participants the inertia data collected at the ankle (used to calculate gait speed) did not record properly, thus only 17 participants and 18 participants respectively are included in these analyses.

4.3.2 Data Collection

Ethical approval was granted for the study in November 2017 by the University of Liverpool’s Ethics Committee (REF: 2672). Five behavioural measures were assessed: head pitch angle, eye angle, muscle coactivation, gait speed and walking smoothness as measured by harmonic ratios. We also measured the duration and number of eye fixations to provide a check of whether eye movements were influenced by wearing the goggles. Eye angle, calculated from vertical pupil movements, and the duration and number of eye fixations, were recorded using a Pupil Labs eye-tracker (Kassner, Patera, & Bulling, 2014). Head pitch, muscle coactivation, gait speed and harmonic ratios were recorded from six Delsys TRIGNO™ Inertia Measurement Unit (IMU) sensors (Boston, MA, USA) placed on participants. Four of these sensors collected inertial data (148Hz) at the head, lower back and superior to both ankles, whilst two sensors collected surface electromyography (sEMG) data (1111Hz) from the *Tibialis Anterior* and medial head of the *Gastrocnemius* muscle of the left leg. Further details of data collection are given in the supplementary material (4.7.1). The lower visual field was blocked using basketball goggles, following the same technique as Rietdyk and Drifmeyer (2009). **Figure 1A** shows an example of the experimental set-up of the head for both full vision and blocked lower visual field conditions. **Figure 1B** shows the approximate extent to which the goggles blocked the participants’ view of lower areas of the scene. Compared to full vision (no goggles), the goggles blocked approximately the lowest 20° of vision when the head was level (see supplementary material 4.7.2 for details).

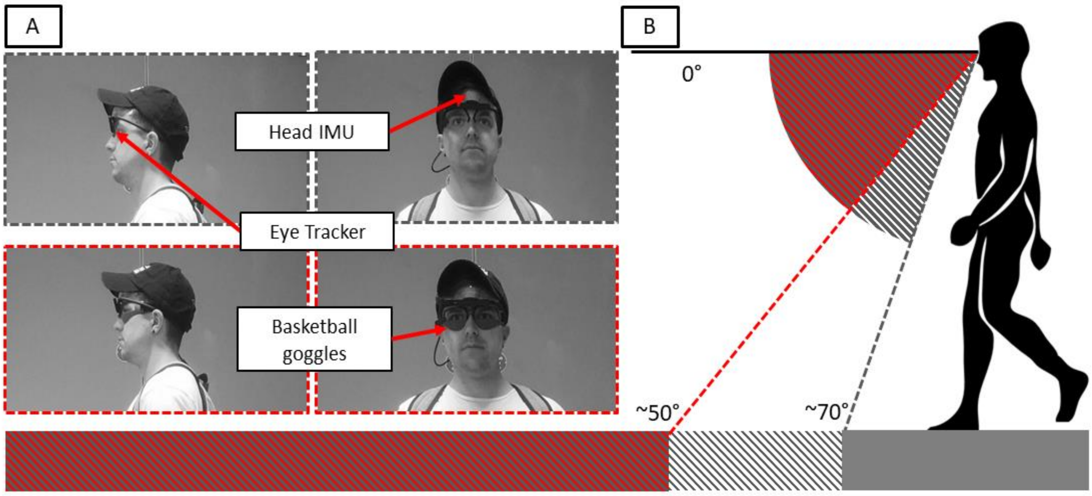

Figure 1: (**A**) Images showing the experimental set-up at the head for the full vision (top) and blocked lower visual field conditions (bottom). Participants wore an eye tracker (used to record eye movements), a head IMU sensor (used to calculate head pitch), basketball goggles (used to block the lower visual field) and a baseball cap (used to shade the eye-tracker during outdoor testing). (**B**) A diagram showing the approximate ranges of negative eye angles from which information about the upcoming surface could be extracted when the head was level. For full vision conditions, negative eye angle ranged from 0° to -70°, (regions striped grey and red), whilst for blocked lower visual field conditions, negative eye angles ranged from 0° to -50° (regions striped red only), see 4.7.2 for details).

4.3.3 Protocol

Participants walked over all of the surfaces with full vision and with a blocked lower visual field. For each of the two vision conditions, participants walked over 14 different surfaces at a self-selected speed. Assignment to the initial vision condition was alternated across participants[2]. As such participants completed either the blocked lower visual field condition first (and, here, completed surfaces in order from A to N), whilst the remaining participants completed the blocked lower visual field condition second (and thus completed surfaces in order from N to A), (see supplementary materials 4.7.3). The surfaces were located across the University of Liverpool campus and are shown in **Figure 2**. The total duration of the study (including debriefing, marker placements, calibrations and the trials themselves) for each participant was approximately 150 minutes of which over 80 minutes was data collection.

For each surface, participants were instructed to look straight ahead whilst standing still in front of the surface for three seconds, then they walked at a comfortable speed across the surface. At the end of the surface, participants again looked straight ahead whilst standing still for a further three seconds. The periods spent looking straight ahead at the start and end of the trial were used to remove drift from the gyroscopic data recorded at the head IMU, vertical gyroscopic data used to calculate head pitch angle. Other than at the start and end of each surface, participants were told that they should move their eyes and head as normal whilst walking.

We tried to ensure that all participant completed the study under similar conditions. Specifically, all participants were tested in the summer, when the University campus was relatively quiet (mid-morning or mid-afternoon), and on dry days. Nevertheless, compared to laboratory-based testing, testing conditions were more variable such that our findings should be relatively robust and relevant to walking outdoors.

Surface complexity for each surface was measured using perceptual ratings of roughness and two ratings of perceived stability as detailed in Thomas, et al. (2020b).

Participants[1] rated surfaces on a Likert scale (Likert, 1932) between 1 (smooth / stable) and 10 (rough / unstable) with participants rating surfaces from vision alone, for perceived roughness and perceived stability, and then participants re-rated perceived stability after having walked on the surface. Surface complexity was taken as the average of the three ratings, given that the ratings were highly correlated (r from 0.94 - 0.98). **Figure 2** shows surfaces ranked from the easiest (S1) to most complex (S14). Perceptual ratings were used as a measure of surface complexity, rather than grouping surfaces together based on similar physical features (smooth, irregular, stairs etc.) due to the inconsistent terminology in the literature using such descriptors (Marigold & Patla, 2007; Matthis & Fajen, 2014; Merryweather, Yoo, & Bloswick, 2011; Patla & Vickers, 2003; Thies, Richardson, & Ashton-Miller, 2005), see Thomas, et al. (2020b) for further discussion. In the present approach, surface complexity is based solely on the participants' evaluations and not on our own.

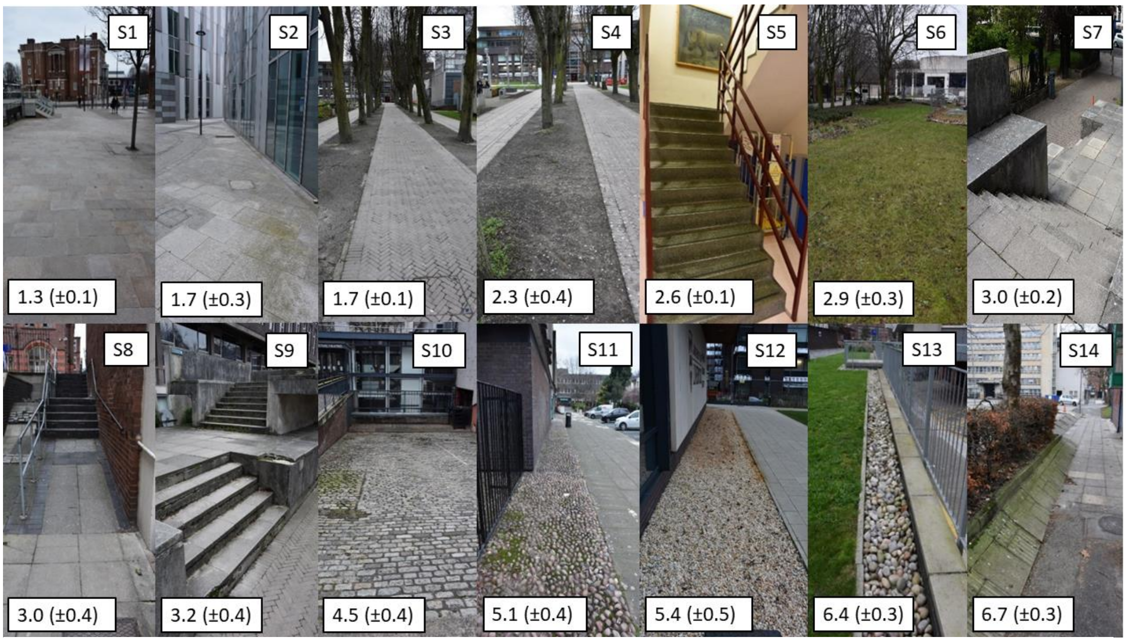

Figure 2: Images showing the 14 surfaces used in the study. Surfaces were ranked based on participants' average perceptual ratings of surface complexity from S1 (smoothest / most stable) to S14 (most complex / hardest to walk over). Average (±SE) perceptual ratings are shown for each surface. See supplementary materials (**Table 4.7.3**) for more information.

4.3.4 Analysis

For each surface, mean head pitch angle, eye angle, muscle coactivation, gait speed and walking smoothness as measured by harmonic ratios were calculated[3]. Head pitch angles were calculated from gyroscopic data from the head IMU with 0° defined as the average position during the three seconds that the participant was static at the start and end of each surface trial. Eye angles of 0° were defined from participant's fixating at a target set at their eye height during calibration of the eye tracker. Deviations from 0° eye angle due to vertical eye movements were converted into angles with eye movements down taken as negative angles. Only eye angles within the normal range expected were analysed (Lee, Kim, Shin, Hwang, & Lim, 2019), for further details see SM2. In addition, eye fixation duration and number of eye fixations were recorded, with fixations defined as stabilised eye movement for at least 100 milliseconds following that of previous research (Marigold & Patla, 2007; Patla & Vickers, 1997, 2003). The average number of eye fixations per metre walked was used to avoid differences caused by the surfaces being different lengths. We also calculated mean relative frequency distributions of head pitch and eye angles for each surface under full vision and blocked lower visual field conditions. Frequencies of head pitch and eye angles were recorded in bins of 5° for each surface. This method follows that of Foulsham, Walker, and Kingstone (2011); Thomas, et al. (2020a). Muscle coactivation was calculated following Winter (2005) for the *Tibialis anterior* and medial head of the *gastrocnemius* muscles across each gait cycle. Gait speed was calculated from gyroscopic data at the ankle following the method from Li, Young, Naing, and Donelan (2010) and known surface lengths, see supplementary material (4.7.3). Walking smoothness was measured in terms of harmonic ratios which were calculated from anteroposterior accelerometery data from the IMU placed at the lower back. A higher ratio was interpreted as a more symmetrical, smoother gait following Bellanca, Lowry, VanSwearingen, Brach, and Redfern (2013).

In order to show how behavioural metrics related to surface complexity, regression analyses were conducted on the participants' mean head pitch angle, eye angle, muscle coactivation, gait speed and walking smoothness. This was done separately for full vision and blocked lower visual field conditions with the independent variable of surface complexity perceptual rating. To compare behavioural changes between the two vision conditions, we conducted t-tests between the regressions' intercepts and slopes. Significant differences were taken as $p<0.05$. Finally, we conducted Pearson's correlations on the mean z-scores of the different measures for each surface. The z-scores for muscle coactivation measures were multiplied by -1 so that, for all five measures, higher z-scores were associated with more stable walking. Large correlations ($r > 0.5$, as determined by Cohen (2013)) are shown in bold for each correlation table. A conservative alpha level of 0.001 was used for correlations, calculated using the Bonferroni correction.

4.4 Results

The behavioural data first reported in Thomas, et al. (2020b) is presented here again as data for full vision conditions. In our previous work these data was used in conjunction with physical and perceptual metrics to analyse different aspects of surface complexity. In the present paper the full vision data was used in combination with previously unpublished data, namely that obtained in the blocked lower visual field condition, to investigate the effect on gait and gaze behaviour of both the availability of visual information and different walking surfaces. Initial analyses revealed that gaze and gait behaviour for the four surfaces with stairs (S5, S7, S8, and S9) differed markedly from that of other surfaces. Despite stairs being typical surfaces found in everyday environments, stairs differ in terms of biomechanics and muscle activation relative to walking over other surface (Cromwell & Wellmon, 2001; Wang, et al., 2017; Zietz & Hollands, 2009). Our results presented here are consistent with that of the previous literature. Due to the distinct patterns shown for stairs, the analysis presented here excluded those four surfaces. We return to address the issue of stairs in the general discussion. To aid comparisons, surfaces with stairs are still plotted on the figures and, for the interested reader, full analyses including stairs are given in the supplementary material (4.7.4).

4.4.1 Head pitch angle

Mean head pitch angles for full vision and blocked lower visual field conditions are shown in **Figure 3A**. A linear regression revealed a significant relation between head pitch and surface complexity for both full vision and blocked lower visual field conditions ($R^2 = 0.881$; $F_{,(1,8)} = 59.43$, *$p < 0.001$* and $R^2 = 0.939$; $F_{,(1,8)} = 122.16$, *$p < 0.001$*) respectively. A t-test between the regression intercepts was not significant, *($t(19) = 1.43$, $p = 0.173$),* however, there was a significant difference between regression slopes *$t(19) = -2.88$, $p = 0.010$).* Head pitch angle for blocked lower visual field conditions showed a greater decrease than that for full vision conditions as surface complexity increased. On the simplest surfaces, head pitch for both conditions was around -5°. However, on the most complex surfaces, head pitch for blocked lower visual field conditions (-22.8°) was around 6° lower than for full vision (-16.8°). Thus, with a blocked lower visual field, participants lowered their head more when surfaces were more complex, compared to with full vision.

4.4.2 Eye angle

Mean eye angle for full vision and blocked lower visual field conditions are shown in **Figure 3B**. A linear regression showed no significant relation between eye angle and surface complexity for full vision ($R^2 = 0.33$; $F_{,(1,8)} = 3.91$, *$p = 0.083$*), however, the equivalent regression for blocked lower visual field conditions was significant ($R^2 = 0.43$; $F_{,(1,8)} = 6.05$, *$p = 0.039$*). A t-test between the regression intercepts was also significant, *($t(19) = 2.34$, $p = 0.033$),* but there was no significant difference between regression slopes *($t(19) = 0.11$, $p = 0.916$.* On average eye angle for full vision (-19.4°) was 4° lower than with blocked lower visual field conditions (-15.4°). However, importantly, this behavioural change occurred irrespective of surface complexity, see **Figure 3B**.

4.4.3 Duration and number of eye fixations

We completed additional analysis to assess the duration and number of eye fixations to check whether these were influenced by blocking the lower visual field. Mean eye fixation duration and the number of eye fixations per metre walked for full vision and blocked lower visual field conditions are shown in **Figures 3C** & **3D**. A linear regression showed no significant relation between the duration of eye fixations and surface complexity for either full vision or blocked lower visual field conditions (R^2 = 0.13; F,(1,8) = 1.24, *p = 0.299* & R^2 = 0.11; F,(1,8) = 0.97, *p = 0.354* respectively). There were also no significant differences between the regression intercepts *(t(19) = -1.14, p = 0.273)* or between regression slopes *(t(19) = 0.21, p = 0.833*. Similarly, a linear regression showed no significant relation between the number of eye fixations and surface complexity for either full vision or blocked lower visual field conditions (R^2 = 0.37; F,(1,8) = 4.69, *p = 0.062* & R^2 = 0.35; F,(1,8) = 4.346, *p = 0.071* respectively). There was also no significant differences between the regression intercepts *(t(19) = 0.58, p = 0.569)* or between regression slopes *(t(19) = 0.20, p = 0.846)*. Thus, increasing surface complexity did not change eye fixation duration or number for either full vision or blocked lower visual field conditions.

Frequencies of eye and head pitch angles were recorded in bins of 5° for each surface following the method of Foulsham, et al. (2011); Thomas, et al. (2020a). The mean frequency distribution for these 5° bins for head pitch and eye angles for both full vision and blocked lower visual field conditions are shown in **Figure 4** for the smoothest surface (S1, top left) to the most complex (S14, bottom right).

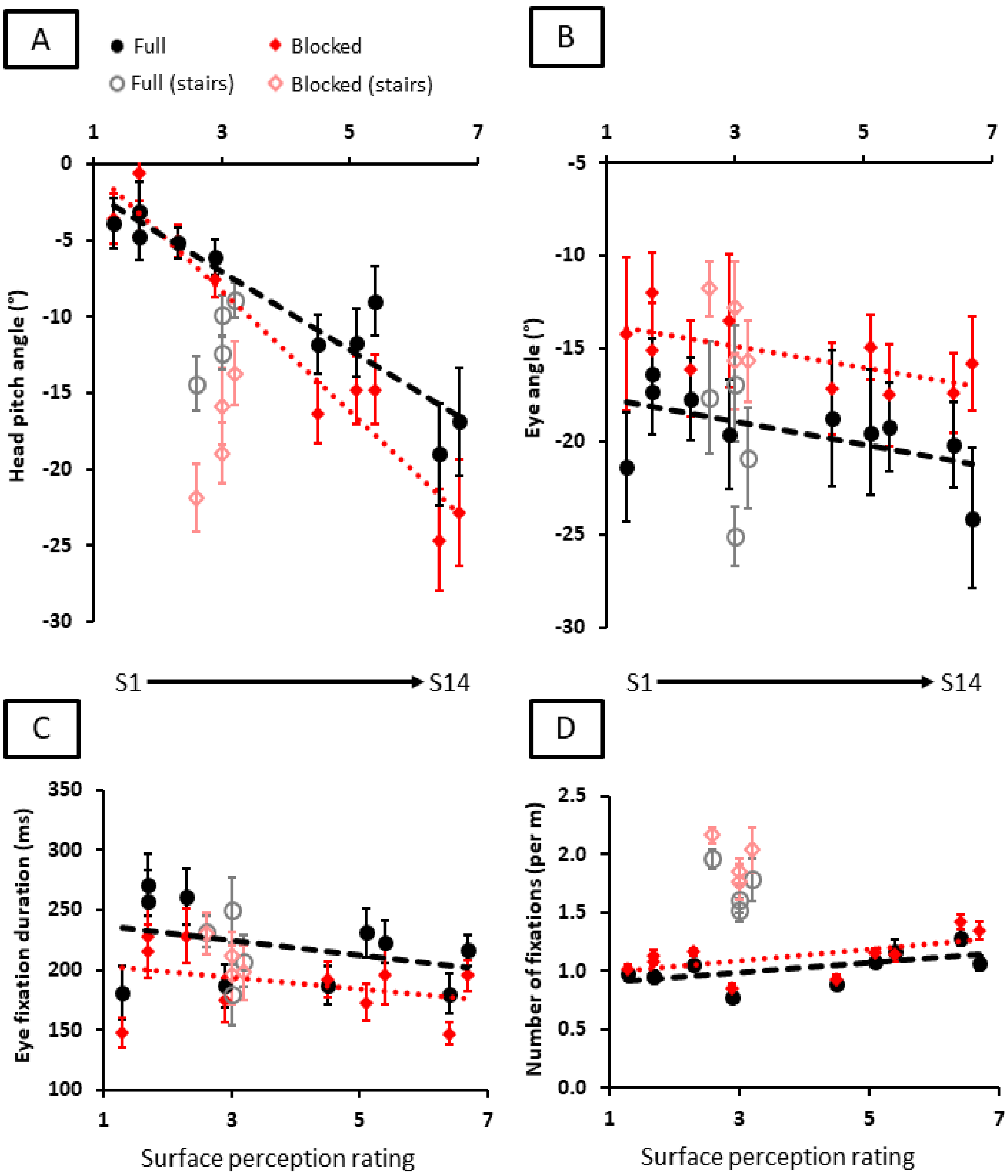

Figure 3: Mean (±SE) (**A**) head pitch angles, (**B**) eye angles, (**C**) eye fixation duration, and (**D**) number of eye fixations per metre walked for surfaces S1 – S14 for full vision (black circles) and blocked lower visual field (red diamonds) conditions. Surfaces with stairs are represented separately (grey open circles and light red open diamonds for full vision and blocked lower visual field respectively). Dotted lines represent the regression lines (when excluding stairs) for full vision and blocked lower visual field conditions.

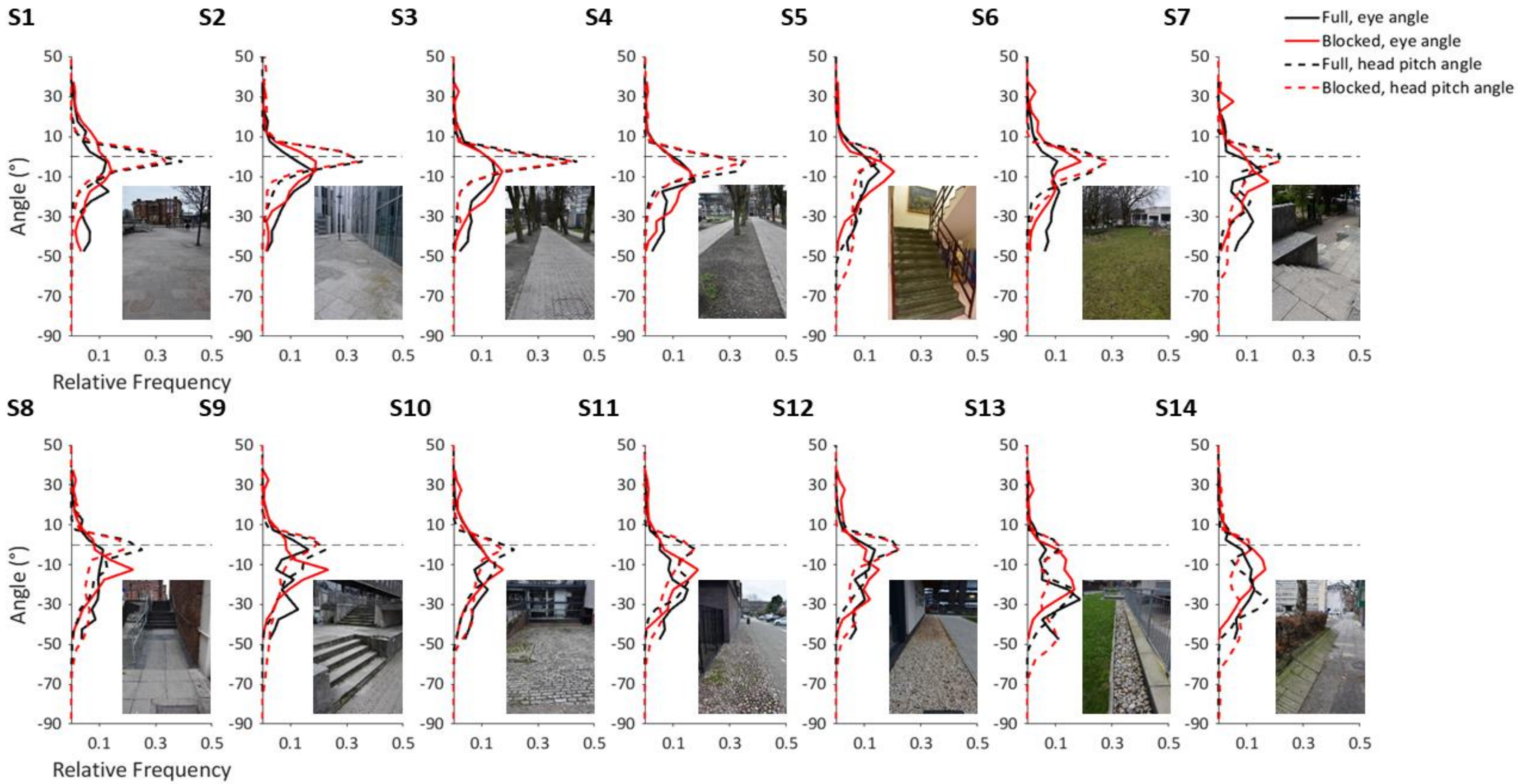

Figure 4: Mean relative frequency distributions of head pitch (dashed line) and eye (solid line) angle for surfaces S1 to S14 under full vision (black) and blocked lower visual field (red) conditions. On the y-axis, results are plotted for 5° bins relative to 0° (looking straight ahead). Negative angles correspond to lowering of the eyes or head toward the ground.

4.4.4 Muscle coactivation

Mean muscle coactivations are shown in **Figure 5A**. A linear regression showed a significant relation between surface complexity and muscle coactivation for both full vision and blocked lower visual field conditions, (R^2 = 0.735; F,(1,8) = 22.18, *p = 0.002* and R^2 = 0.596; F,(1,8) = 11.82, *p = 0.009* respectively). However, there was no significant difference between the regressions intercepts or slopes (*t(19) = 1.39, p = 0.183* and *t(19) = 0.58, p = 0.573* respectively). Thus, increasing surface complexity increased muscle coactivation to a similar extent for full vision and blocked lower visual field conditions.

4.4.5 Gait speed

Mean gait speeds are shown in **Figure 5B**. A linear regression showed a significant relation between surface complexity and mean gait speed for both full vision and blocked lower visual field conditions, (R^2 = 0.761; F,(1,8) = 25.524, *p = 0.001* and R^2 = 0.688; F,(1,8) = 17.606, *p = 0.003* respectively). However, there was no significant difference between the two regression intercepts or slopes, (*t(19) = 0.41, p = 0.686* and *t(19) = 0.09, p = 0.926* respectively). Thus increasing surface complexity reduced gait speed to a similar extent for full vision and blocked lower visual field conditions.

4.4.6 Walking smoothness as measured by mean harmonic ratios

Mean anteroposterior harmonic ratios are shown in **Figure 5C**. A linear regression showed a significant relation between surface complexity and walking smoothness from mean harmonic ratios for both full vision and blocked lower visual field conditions (R^2 = 0.888; F,(1,8) = 63.29, *p < 0.001* and R^2 = 0.813; F,(1,8) = 34.71, *p < 0.001* respectively). However, there was no significant difference between the two regression intercepts or slopes, ($t(19) = -0.68$, $p = 0.507$ & $t(19) = 0.48$, $p = 0.638$ respectively). Thus, increasing surface complexity reduced harmonic ratios to a similar extent for full vision and blocked lower visual field conditions.

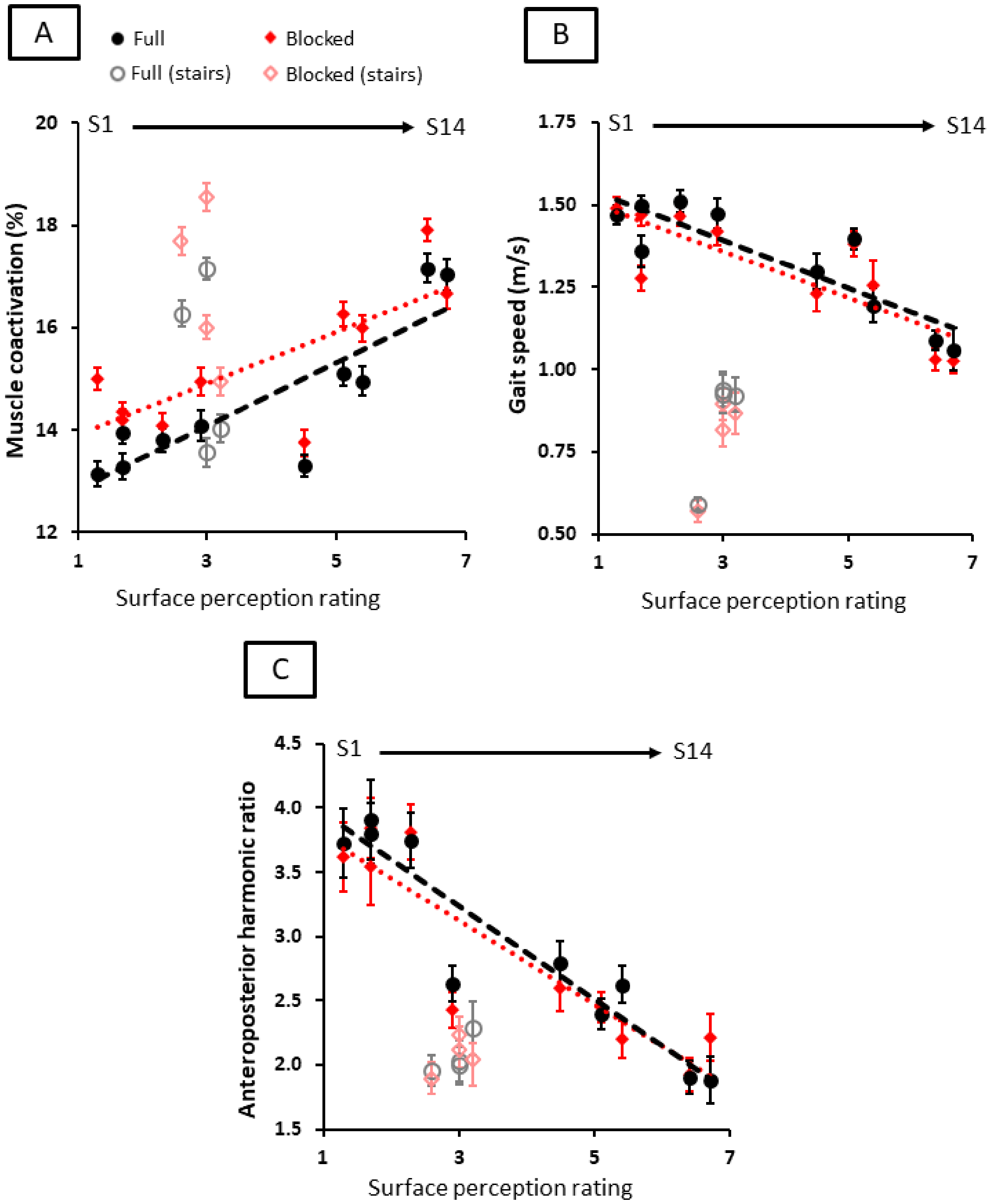

Figure 5: Mean (±SE) (**A**) muscle coactivation, (**B**) gait speed and (**C**) anteroposterior harmonic ratio used to measure walking smoothness for surfaces S1 – S14 for full vision (black circles) and blocked lower visual field (red diamonds) conditions. Surfaces with stairs are represented separately (grey open circles and light red open diamonds respectively). Dotted lines represent the regression lines (when excluding stairs) for full vision and blocked lower visual field conditions.

We also conducted a regression on the z-scores for each surface averaged over multiple measures to check if this provided a less noisy and more sensitive measure of the influence of blocking the lower visual field than the separate analyses of individual measures reported above. This was not found to be the case, see the supplementary material (4.7.5), with no significant difference between either the regression intercepts or slopes for full vision versus blocked lower visual field. Finally, Pearson's correlations were conducted on the mean z-scores of the different gaze and gait measures for each surface, first comparing full vision to blocked lower visual field, (see supplementary materials **Table 4.7.6.1**), then comparing the different measures for full vision (see supplementary materials **Table 4.7.6.2**), and for blocked lower visual field (see supplementary materials **Table 4.7.6.3**). For both visual conditions, head pitch and gait measures (muscle coactivation, gait speed and walking smoothness as measured by harmonic ratios) were more strongly correlated with each other than eye angle, fixation duration and number of fixations.

4.5 Discussion

Surfaces that were rated as rougher and less stable to walk on were associated with significant changes for both visual conditions (full vision and blocked lower visual field conditions). On more complex surfaces head pitch lowered, muscle coactivation increased, gait slowed and walking smoothness as measured by harmonic ratios was reduced. Thus, surface complexity had wide-ranging effects on both gaze and gait. However, head pitch angle was the only measure that showed a significant synergistic interaction from the effect of blocking the lower visual field. The head lowered more when both the lower visual field was blocked and people walked over more complex surfaces compared to the sum of the individual effects of both factors, see Fig 3A.

Gaze and gait behaviour showed clear differences when walking over more complex surfaces for both visual conditions. These results are in line with those reported in previous studies which have assessed gaze and gait across more challenging conditions ('t Hart & Einhauser, 2012; Marigold & Patla, 2007, 2008a; Matthis, et al., 2018). In conjunction, these behavioural changes provide converging evidence that stability decreases when walking over more complex surfaces. As discussed in the introduction, given the current lack of a gold standard metric for stability (see Bruijn, et al., 2013), using a diverse range and number of measures, as shown here, may provide a robust and sensitive indication of stability and therefore fall risk when walking.

Surface type had a greater impact on gaze and gait behaviour than blocking the lower visual field. Extrinsic factors, including the environment, are likely to be the predominant risk of falling in young healthy individuals (Berg & Cassells, 1990). In contrast, the elderly have intrinsic factors, affecting body functions, that increase their risk of falls (as reviewed in Pynoos, Steinman, & Nguyen, 2010). Understanding how vision affects stability is essential, given that elderly people with visual impairments report additional perceived risks of falling relative to elderly people without visual impairments (Brundle, et al., 2015). In the present study the lack of behavioural changes when blocking the lower visual field, other than to head pitch and eye angle, suggests that young people are relatively robust to challenges to their locomotion. However, unlike in our study, Marigold and Patla (2008b) reported that gait speed reduced when the lower visual field was blocked. This discrepancy in findings may be because the surfaces used by Marigold and Patla (2008b) were more challenging given their multi-surface type composition. As such, this may indicate that young people need highly challenging conditions to reduce their stability. In support of this, studies that have included simulations of multiple intrinsic factors related to falling (e.g. both physical and cognitive impairments) have shown that young people adopt a cautious gait (Granacher, Wolf, Wehrle, Bridenbaugh, & Kressig, 2010; Hollman, Kovash, Kubik, & Linbo, 2007). Therefore, future studies investigating the factors influencing fall risk and walking stability in the elderly should either assess how young people cope with simulations of several concurrent impairments, representative of age-related co-morbidities, or directly assess behaviour indicative of stability in elderly populations.

Blocking the lower visual field only produced effects that interacted with surface complexity for one of our five measures, namely head pitch angle. This may indicate that we prioritise a relatively easy change (tilting the head down) over more energetically costly changes elsewhere in the body when walking on more complex surfaces. This would suggest that our initial tactic, when confronted with the challenge of walking on complex surfaces, is to improve the visual information available about the surfaces rather than altering our gait. Interestingly, previous research that has used goggles to block the lower visual field has not shown a lowering of head pitch in the young when stepping over obstacles (Muir, Haddad, Heijnen, & Rietdyk, 2015). Similarly multifocal spectacle wearers do not alter head pitch based on different lenses worn (Timmis, Johnson, Elliott, & Buckley, 2010). However, we assessed walking outside across complex surfaces, whereas this previous research focused on time-locked, short duration responses, including obstacle or step negotiation, performed predominately in laboratory-based settings. Other research has found different responses to simulated visual deficits. For example, Zult, Allsop, Timmis, and Pardhan

(2019) found that, when stepping over an obstacle with blurred vision, single stance support time as well as eye fixations increased compared to normal vision. Similarly, studies simulating monocular vision found that gait slowed and toe clearance increased when stepping over an obstacle, indicating a more cautious gait (Hayhoe, Gillam, Chajka, & Vecellio, 2009; Patla, Niechwiej, Racco, & Goodale, 2002). These differing results could indicate that lower visual field loss, as tested in the present study, has less effect on gait than other visual factors (e.g. blurred or monocular vision). However, alternatively, it may be that gait changes are more pronounced when people step over an obstacle rather than when they walk along a complex surface. Obstacle avoidance requires one-off adjustments to gait and, here, visual deficits may be more disruptive (Friedman, et al., 2007; Jansen, Toet, & Werkhoven, 2010; Lajoie, et al., 2018; Timmis & Buckley, 2012). As an example of this, Patla (1998) demonstrated that, when stepping over an obstacle, toe clearance increased and participants positioned their feet further from the obstacle when their lower visual field was blocked. In combination with findings at the head from Muir, et al. (2015); Timmis, et al. (2010), this suggests that when vision from the lower visual field is unavailable, eye and gait behaviour suffice to cope with immediate gait demands (obstacle negotiation), whereas head position is used to cope with long term challenges (e.g. uneven surfaces).

Changes in head pitch angle per se may influence the chance of falling in more challenging outside environments. This is because normally, with a flexed head position, people’s gaze will centre on the ground plane surrounding their upcoming footsteps. This, in turn, means that people are less able to extract visual information from their wider surroundings, including street furniture, pedestrians and vehicles. A lowered head (typical of a flexed posture) is known to be associated with lower functional status (ability to perform normal daily activities) in elderly women (Balzini, et al., 2003). Our test surfaces were located away from roads, crowds and static obstacles so this did not cause a problem for our participants. Nevertheless, such challenges are commonplace in everyday situations. The relative frequency plots (**Figure 4**) in effect show the variance of eye and head pitch angles throughout the trial. Head pitch was nearly horizontal for much of the time spent walking on less complex, smoother surfaces under both full vision and blocked lower visual field. Here, participants could readily scan their surroundings. However, for the most complex surfaces, head pitch angle was both more variable and generally lower. In comparison, eye angle remained relatively constant under the two conditions regardless of surface complexity (see supplementary material 4.7.7). Together these results suggest that participants were moving their head more when coping with more complex surfaces. Though not traditionally interpreted as a measure of stability, these changes to head pitch support the hypothesis that gaze angle (especially due to head movements) can be used to assess the complexity of a surface when walking (Thomas, et al., 2020a).

One notable finding of the study was that stairs skewed most of our behavioural measures. Only for eye angle and eye fixation duration did the four surfaces with stairs (S5, S7, S8 and S9) produce behaviour similar to that of the other surfaces. The distinct behaviour for stairs was not surprising given previous research comparing walking up stairs to level walking (Cromwell & Wellmon, 2001; Wang, et al., 2017; Zietz & Hollands, 2009). Stair walking has been researched with respect to gaze behaviour, biomechanics and muscle activity (e.g. Hinman, Cowan, Crossley, & Bennell, 2005; Miyasike-DaSilva, Allard, & McIlroy, 2011; Reeves, Spanjaard, Mohagheghi, Baltzopoulos, & Maganaris, 2008). Our results suggest that our surface complexity metric based on perceptual ratings may be inappropriate for stairs and that, instead, stairs might be better characterised based on physical measurements (Thomas, et al., 2020b). We have, nevertheless, shown the results for stairs in both our figures and in the analyses reported in the supplementary materials, given that our aim was to test a broad range of surfaces typically encountered in everyday life. Furthermore it is important to understand the interaction between gaze and gait on stairs given that they are a common cause for falls, including for those with visual impairments (Pan, Liu, Sun, & Xu, 2015).

4.6 Conclusion

In summary, we found that many aspects of gaze and gait altered as surface complexity increased. In general, for our young, healthy participants the effects of surface complexity were not exacerbated by blocking the lower visual field. The only exception was for head pitch angle whereby the head lowered more on more complex surfaces if, in addition, the lower visual field was blocked. This finding illustrates the complexity of considering the effects of both extrinsic factors (e.g. surface complexity) and intrinsic factors (e.g. limiting visual information) on fall risk. Our study suggests that young people cope well with a reduction in information from their lower visual field even when walking over challenging surfaces. However, only one intrinsic factor was simulated here. Future research should see whether alternative or additional manipulations, representative of the comorbidities experienced by the elderly, change walking over surfaces of varying complexity. This would allow us to build up a more accurate understanding of how our gait responds to both extrinsic and intrinsic challenges.

4.7 Supplementary materials

4.7.1 Detailed description of methodology

This description is based on that originally given in (Thomas, et al., 2020b)

Additional data collection information

The eye-tracker was calibrated prior to the participants walking over the 14 surfaces used in this study. Eye movements and eye fixations were recorded using a Pupil Labs eye-tracking headset (Kassner, et al., 2014) that recorded pupil movement at 30Hz and a world view at 60Hz. We were interested in how the stability of walking on surfaces influenced vertical gaze so we only analysed pupil movement in the vertical direction. Only eye angles between +40° to -70° were included based on previous research by Lee, et al. (2019). 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 148Hz. 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, et al. (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.

Additional analysis information

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, 10Hz 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 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 all behavioural measures the first two and last two strides for each surface were removed from the mean calculation to avoid the influence of starting and stopping walking. Z-scores of means were then calculated using the mean and standard deviation value from each measure.

4.7.2 Eye angle blocked from goggles

We completed a small study to determine the extent to which the goggles blocked visual inputs relative to full vision. Ten healthy adults (5 male, mean ± SD; age = 27.4 ± 1.1 years; height = 175 ± 9.2cm) were told to fixate targets across a range of eye angles (from looking directly ahead, 0°, to looking down at -70°). Participants kept their head still and level, whilst fixating at targets set incrementally (every 10°) starting from a target set at their eye height (defined as 0°). Participants were asked to report if they were unable to fixate at a target without moving their head. All 10 participants were able to fixate all the targets under full vision conditions. However, when wearing the goggles only 7 participants were able fixate at the target at -30°, 6 participants at -40° target, 1 participant at -50° target and none at the -60° or -70° targets. Thus, the goggles blocked around 20° to 40° of the visual scene compared to full vision conditions.

4.7.3 Surface descriptions, order completed and lengths

Table 4.7.3: Descriptions, order in which the surfaces were tested and surface lengths (to the nearest metre) for the 14 surfaces. See **Figure 2** for images of each surface.

Surface label	Description of the surface	Order of completion (A to N/N to A)	Approximate length (metres)
S1	Flagstone paving	D	31
S2	Flagstone paving	A	29
S3	Brick paving	G	31
S4	Fine gravel	H	30
S5	38 indoor, polished stairs including three landings	N	15
S6	Rough grass	J	34
S7	13 concrete stairs including two landings (descending)	L	10
S8	11 outdoor concrete stairs including two landings	C	13
S9	13 concrete stairs including two landings (ascending)	K	10
S10	Brick slope	F	35
S11	Stones set in concrete	M	31
S12	Small, loose pebbles	I	19
S13	Loose stones	E	30
S14	Oblique paved slope	B	29

4.7.4 Results including stairs

Head pitch angle

Mean head pitch angles were calculated for full vision and blocked lower visual field conditions on surfaces S1 – S14. A linear regression revealed a significant relation between surface complexity and head pitch angle for both full vision (R^2 = 0.638; F,(1,12) = 21.12, *p = 0.001*) and blocked lower visual field conditions (R^2 = 0.564; F,(1,12) = 15.54, *p = 0.002*). However, there were no significant differences between the two regression intercepts or slopes, *(t(27) = 1.11, p = 0.279 and t(27) = 0.09, p = 0.926).*

Eye angle

Mean eye angles were calculated for full vision and blocked lower visual field conditions on surfaces S1 – S14. A linear regression showed no significant relation between eye angle and surface complexity for full vision (R^2 = 0.148; F,(1,12) = 2.087, *p = 0.174*), however the equivalent regression for blocked lower visual field conditions was significant (R^2 = 0.373; F,(1,12) = 7.13, *p = 0.020*).

Duration and number of eye fixations

Mean eye fixation number and fixation duration were calculated for full vision and blocked lower visual field conditions on surfaces S1 – S14. A linear regression showed no significant relation between the duration of eye fixations and surface complexity for either full vision (R^2 = 0.10; F,(1,12) = 1.37, *p = 0.265)* or blocked lower visual field conditions (R^2 = 0.14; F,(1,12) = 2.02, *p = 0.181*). Similarly, a linear regression showed no significant relation between the number of eye fixations and surface complexity for either full vision ((R^2 = 0.0004; F,(1,12) = 0.004, *p = 0.950)* or blocked lower visual field conditions (R^2 = 0.0006; F,(1,12) = 0.007, *p = 0.935*).

Muscle coactivation

Mean muscle coactivations were calculated for full vision and blocked lower visual field conditions on surfaces S1 – S14. A linear regression revealed a significant relation between muscle coactivation and surface complexity under full vision (R^2 = 0.372; F,(1,12) = 7.10, *p = 0.021*), however, the equivalent regression for blocked lower visual field conditions was not significant (R^2 = 0.180; F,(1,12) = 2.638, *p = 0.130*).

Gait speed

Mean gait speed was calculated for full vision and blocked lower visual field conditions on surfaces S1 – S14. A linear regression revealed no significant relation between gait speed and surface complexity for either full vision (R^2 = 0.049; F,(1,12) = 0.617, *p = 0.447)* or blocked lower visual field (R^2 = 0.038; F,(1,12) = 0.469, *p = 0.506*).

Walking smoothness as measured by harmonic ratios

Mean anteroposterior harmonic ratios were calculated in order to provide an estimate of walking smoothness. Ratios were calculated for full vision and blocked lower visual field conditions on surfaces S1 – S14. A linear regression revealed a significant relation between harmonic ratios and surface complexity for both full vision (R^2 = 0.428; F,(1,12) = 8.98, *p = 0.011*) and blocked lower visual field conditions (R^2 = 0.394; F,(1,12) = 7.79, *p = 0.016*). However, there were no significant differences between the two regression intercepts or slopes, *(t (27) = 0.22, p = 0.832* and *t(27) = 0.30, p = 0.766* respectively).

4.7.5 Comparing average z-scores

We conducted a regression on the z-scores averaged across four behavioural measures (head pitch angle, gait speed, walking smoothness as measured by harmonic ratios and muscle coactivation) for each surface. We did not include eye angle, eye fixation duration or eye fixation number in this analysis due to their weak correlations with the other measures (see Supplementary Materials 4.7.6). As noted in the methodology section, z-scores were multiplied by -1 for muscle coactivation so that higher z-scores were always associated with more stable walking. The average (± SE) z-scores for the different surfaces are shown in **Figure 4.7.5**. When including all 14 surfaces there was no significant difference between regression intercepts or slopes for full vision versus blocked lower visual field conditions, *(, t(27) = -0.37, p = 0.715* and *t(27) = 0.28, p = 0.780) respectively*. This was also the case when excluding stairs, *(t(19) = 0.53, p = 0.604* and *t(19) = -0.97, p = 0.345* respectively).

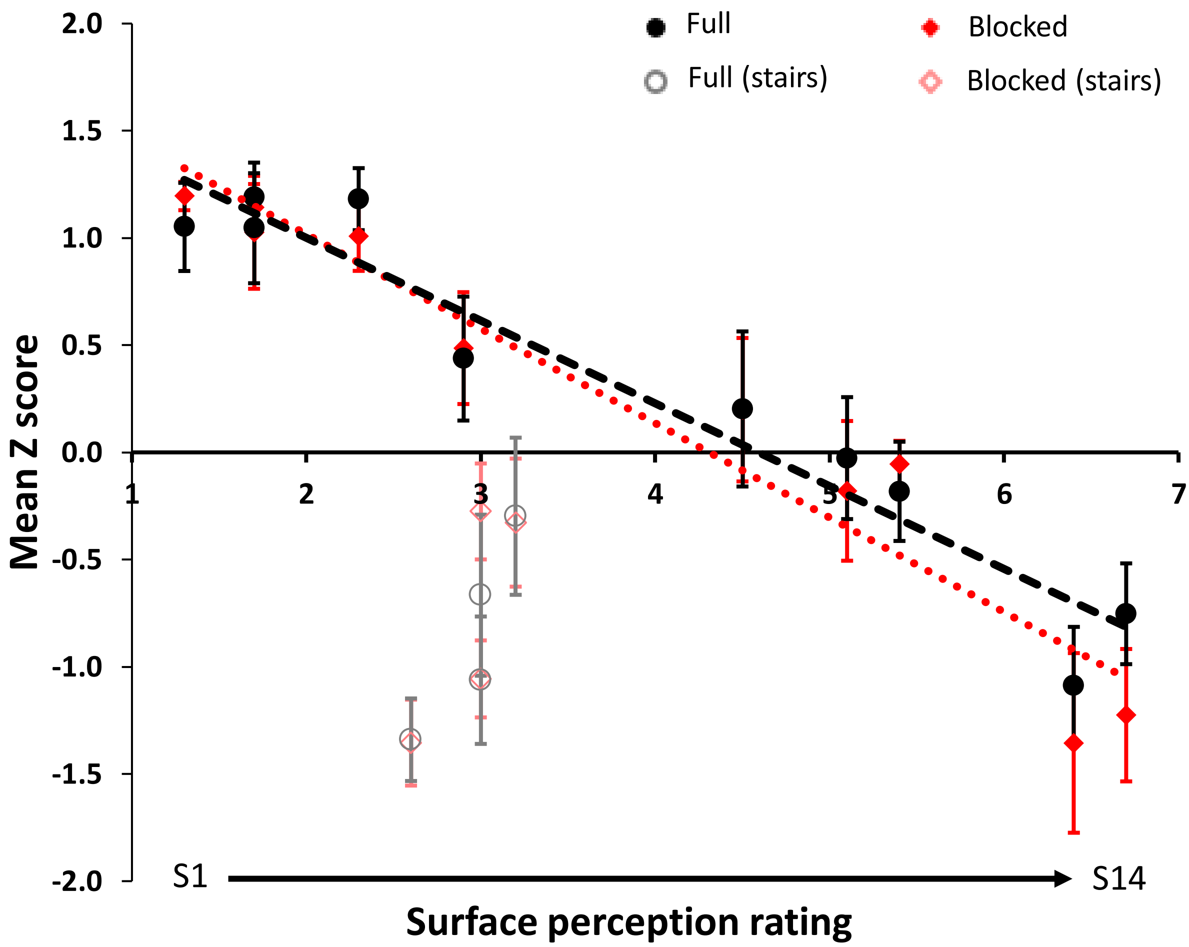

Figure 4.7.5: Mean (±SE) average z-scores across four of the behavioural measures (head pitch angle, gait speed, walking smoothness as measured by harmonic ratios and muscle coactivation) for ten of the fourteen surfaces for full vision (black circles) and blocked lower visual field (red diamonds) conditions. The four surfaces with stairs are represented separately (grey open circles and light red open diamonds). Dotted lines represent the regression lines (when excluding stairs) for full vision and blocked lower visual field. The linear regression equations are as follows: full vision = R^2 = 0.93 (y = -0.39x + 1.77) and blocked lower visual field conditions = R^2 = 0.93 (y = -0.44x + 1.90).

4.7.6 Pearson's correlations between mean z-scores across the 14 surfaces for the seven gaze and gait behavioural measures.

Table 4.7.6.1: Pearson's correlations between mean z-scores for full vision versus blocked lower visual field conditions. * signifies a significant correlation of *p <0.001 (*as determined by the Bonferroni correction) , bold values signify large correlations (r > 0.5) as determined by Cohen (2013).

Head pitch angle	Eye angle	Eye fixation duration	Number of eye fixations	Muscle coactivation	Gait speed	AP harmonic ratio
0.97*	0.05	**0.76**	**0.97***	**0.97***	**0.99***	**0.91***

Table 4.7.6.2: Pearson's correlations between mean z-scores for the seven behavioural measures for full vision conditions only. * signifies a significant correlation of *p <0.001 (*as determined by the Bonferroni correction) , bold values signify large correlations (r > 0.5) as determined by Cohen (2013)

	Eye angle	Eye fixation duration	Number of eye fixations	Muscle coactivatio n	Gait speed	AP harmonic ratio
Head pitch angle	0.43	0.39	-0.24	**0.80***	**0.62**	**0.85***
Eye angle	-	**0.61**	0.21	**0.60**	0.23	0.46
Eye fixation duration	-	-	0.01	0.32	0.12	0.42
Number of eye fixations	-	-	-	-0.05	0.38	0.19
Muscle coactivatio n	-	-	-	-	**0.57**	**0.68**
Gait speed	-	-	-	-	-	**0.78***

Table 4.7.6.3: Pearson's correlations between mean z-scores for the seven behavioural measures for blocked lower visual field conditions only. * signifies a significant

correlation of *p <0.001 (*as determined by the Bonferroni correction) , bold values signify large correlations (r > 0.5) as determined by Cohen (2013)

	Eye angle	Eye fixation duration	Number of eye fixations	Muscle coactivation	Gait speed	AP harmonic ratio
Head pitch angle	0.21	0.18	-0.29	**0.77**	**0.72**	**0.87***
Eye angle	-	0.32	0.19	0.16	-0.11	0.17
Eye fixation duration	-	-	-0.21	0.22	-0.24	0.22
Number of eye fixations	-	-	-	-0.14	0.31	0.15
Muscle coactivation	-	-	-	-	**0.65**	**0.73**
Gait speed	-	-	-	-	-	**0.74**

4.7.7. Overall relative frequency plot

Figure 4.7.7 shows the overall mean relative frequency plots, averaging across the 14 different surfaces.

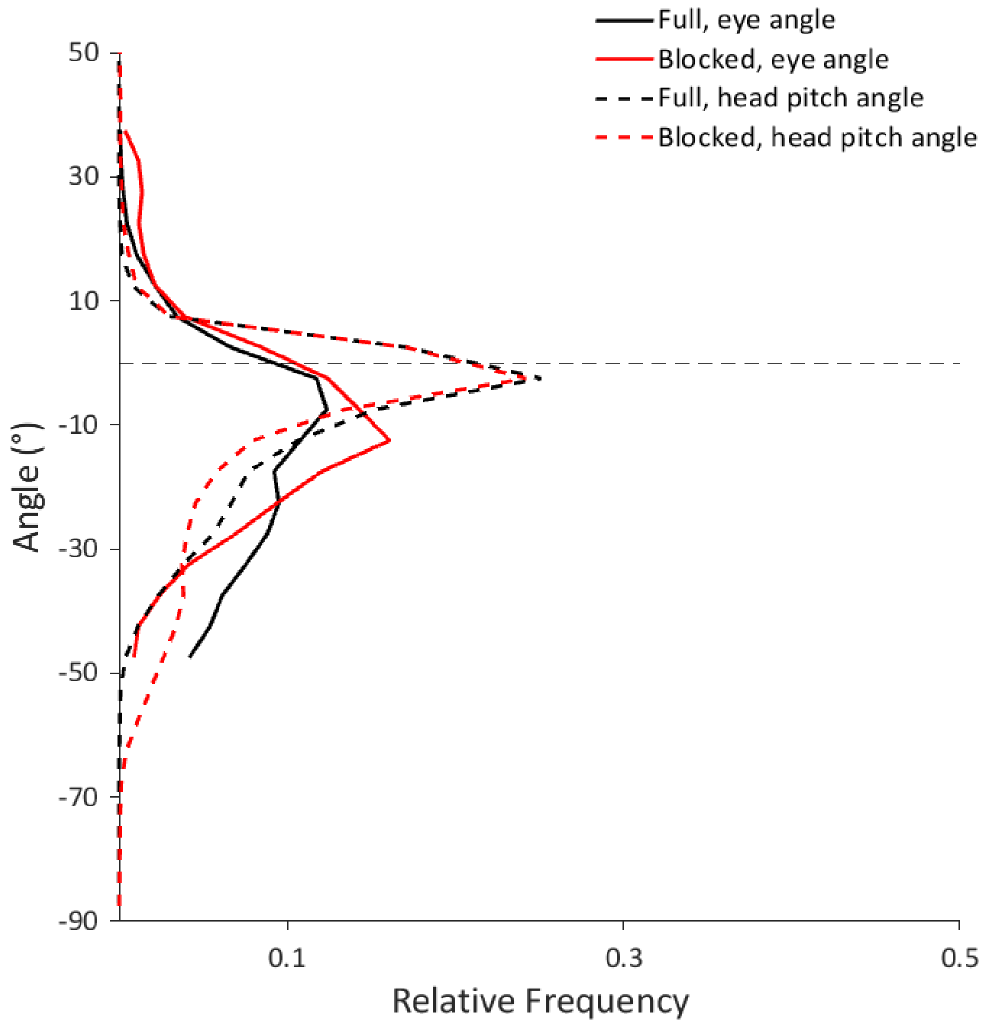

Figure 4.7.7: Overall mean relative frequency distributions of head pitch (dashed line) and eye (solid line) angle across the 14 surfaces under full vision (black) and blocked lower visual field (red) conditions. On the y-axis, results are plotted for 5° bins relative to 0° (looking straight ahead). Negative angles correspond to lowering of the eyes or head toward the ground.

Footnote:

[1] Full details of the perceptual rating study are provided in Thomas, et al. (2020b). In brief, 32 participants (14 male, mean ± SD; age = 22.2 ± 5.0 years; height = 172.6 ± 8.5cm), completed the perception rating study. Twelve of these participants had been participants in the present study (10 male, age = 27.3 ± 4.3 years; height = 178.0 ± 6.9cm). There were no significant differences between the mean responses for the participants who completed both studies and the remaining 20 participants, ($F(1, 32) = 0.22$, $\eta_p^2 = 0.01$, $p = 0.643$) so responses were pooled together.

[2] As the attachment and removal of sensors and initial eye calibration had to be completed in the gait laboratory, for practical reasons of locations and sensor battery life, all participants started by completing surfaces from A through to N and then they completed surfaces N though to A.

[3] One limitation of the study was that we were only able to collect data for participants walking once over a given surface for each of the two visual conditions. This was due to the time taken to complete the study and the limited battery life for the IMU sensors used in the study. However, for each condition and for all surfaces we collected eye, inertia and EMG data at high frequencies (between 30Hz and 1111Hz) for our five behavioural measures, for each condition and for all surfaces. We collected over 80 minutes of data per participant and mean values per trial were based on averages over hundreds of values.

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Chapter Five: The influence of cognitive load and lower visual field loss on gaze and gait

In the previous chapters I have shown how surface complexity affects both gaze and gait behaviour (chapters 2 – 4). However, young people have been shown to be relatively robust to a singular intrinsic factor of simulated loss of their lower visual field (chapter 4). One possible reason for the difference between our results and the known fall risk associated with age is that only one age-related deficit was simulated. Older people typically have numerous comorbidities, so simulations of multiple deficits are more likely to cause behavioural changes indicative of that found with age. As well as visual field loss, a common deficit found in the elderly is a reduced cognitive capacity. This is known to reduce stability when walking (Woollacott & Shumway-Cook, 2002). Simulated cognitive deficits are often used to mimic age-related impairments in young people (Bahureksa, et al., 2017). The aim in this chapter was to simulate reduced cognitive capacity on its own and in combination with simulated lower visual field loss. This was done to investigate whether simultaneously simulating *two* age-related deficits produced deficits in gait and gaze behaviour similar to those observed for older adults with multiple comorbidities.

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The primary author conceived and designed the experiments, conducted the experiments, analysed the data, prepared the figures and tables and authored the draft in preparation.

5.1 Abstract

Background: Age-related health deficits affect gaze and gait behaviour whilst walking, especially over challenging surfaces. Simulating deficits in cognitive capacity and visual fields can reveal how cognitive and visual factors influence gaze and gait. However, simulating one deficit alone may not provide a good model of the multiple comorbidities typically experienced by older people. In the present study we simulated both cognitive and visual deficits simultaneously in young, healthy adults whilst also varying an environmental factor.

Methods: Participants walked over 20 surfaces that varied in complexity whilst wearing a mobile eye-tracker and inertia measurement unit sensors. We assessed how an increased cognitive load and reduced information from the lower visual field influenced eye angle, the number and duration of fixations, head pitch angle, gait speed and walking smoothness.

Results: Surface complexity had substantial effect on behaviour: more complex surfaces caused behavioural changes in all measures except for eye angle. In contrast, combining the two intrinsic factors produced few functionally significant effects on gaze and gait behaviour regardless of surface complexity. Individually, the two deficits did have some effects. A blocked lower visual field changed gaze behaviour and produced a more asymmetric gait but these changes were modest relative to the effects of surface complexity. An increased cognitive load had only marginal effects on gait speed.

Significance: Surface complexity had a greater effect on behaviour than blocking the lower visual field or increasing cognitive load and there were few meaningful interactions between different deficits. This suggests that, when walking outdoors,

young people may be relatively robust to multiple simulated deficits whereas the gaze and gait of older people deteriorates with multiple comorbidities. Thus, simulating deficits common in older people should be used with caution.

5.2 Introduction

At all ages, most falls occur outdoors and when people walk over complex surfaces (Li, et al., 2006; Talbot, Musiol, Witham, & Metter, 2005), so we can assume that gait is more unstable here. Outdoors, we typically encounter more challenging and varied conditions, often including different surface types. Studies have shown that, when walking over more complex outdoor surfaces, gaze is lowered toward the body, steps are shorter and gait is slower and less symmetrical ('t Hart & Einhauser, 2012; Matthis, Yates, & Hayhoe, 2018; Thomas, Gardiner, Crompton, & Lawson, 2020a, 2020b). These behavioural changes are all either associated with increased perceived fall risk or are indicative of more risky behaviour associated with falls (Doi, et al., 2013; Marigold & Patla, 2007, 2008a; Menz, Lord, & Fitzpatrick, 2003; Peterson & Martin, 2010; Voloshina, Kuo, Daley, & Ferris, 2013). In our previous work we have focussed on the challenges presented to the walker due to complex, outdoor surfaces such as uneven ground, slopes and steps, and the influence on walking of a single, simulated, age-related deficit, namely lower visual field loss. Our results showed that walking over more complex surfaces was associated with changes in gaze (for example, lowering the head) and gait (for example, slower and more asymmetric gait) (Thomas, et al., 2020b; Thomas, Gardiner, Crompton, & Lawson, 2020c). However, young, healthy people appeared to adapt well to occlusions of their lower visual field, making minimal changes to their gaze and gait (Thomas, et al., 2020a). We reasoned that our young, healthy participants may not have been sufficiently challenged by our experimental manipulations. In our previous studies the combination of challenges that were intrinsic (blocking the lower visual field) and extrinsic (walking over complex surfaces) still did not match the severity of the combined deficits that are commonly encountered as we age.

Building on our previous work, in the present paper we assessed the effects of a distinct, non-environmental, yet ubiquitous challenge to gait over complex surfaces, namely the increased cognitive load arising from performing a concurrent load task. In doing so, we can simulate two common, age-related deficits, namely cognitive decline and reduced peripheral vision (Beurskens & Bock, 2012; Brayne, 2007; Collins, Brown, & Bowman, 1989; Crassini, Brown, & Bowman, 1988; Jorm & Jolley, 1998). Both deficits are intrinsic factors (i.e. related to the individual) that are known to affect gait stability (Black, Wood, & Lovie-Kitchin, 2011; Hausdorff, Schweiger, Herman, Yogev-Seligmann, & Giladi, 2008; Laessoe, Hoeck, Simonsen, & Voigt, 2008; Woollacott & Shumway-Cook, 2002) and which may interact in an unpredictable fashion. Below, we will review what is known about how these two intrinsic factors impact gaze and gait behaviour and, in turn, fall risk, and the influence of the extrinsic factor of surface complexity on those impacts.

5.2.1 Reduced Peripheral Vision and Surface Complexity

Deterioration in peripheral vision is a well-studied, age-related, disorder that is associated with an increased fall risk (Black, et al., 2011; Collins, et al., 1989). Furthermore, loss of peripheral vision is a common symptom of age-related diseases such as glaucoma. Several studies have investigated how simulated loss of the lower peripheral visual field affects gait stability in otherwise healthy young people. For example, simulated lower visual field loss caused young individuals to adopt a more cautious gait, including a lowered head pitch angle, slower walking speed and reduced accuracy of foot placement, when walking on more complex surfaces (Graci, Elliott, & Buckley, 2010; Marigold & Patla, 2008b; Rietdyk & Drifmeyer, 2009). These studies tested walking in a laboratory and over a limited variety of surfaces. In contrast, in our own research (Thomas, et al., 2020a) participants walked over a wide range of outdoor, everyday surfaces, thus increasing experimental ecological validity. We found that gait remained relatively unchanged when blocking the lower visual field of young people, but that head pitch angle lowered, especially over more complex surfaces.

5.2.2 Cognitive Decline and Surface Complexity

Every day walking is often paired whilst concurrently performing various secondary tasks such as route-finding, talking, using a mobile phone or listening to music. However, as we get older, our ability to execute concurrent tasks whilst walking is compromised. This has been shown to result in both worse performance for the concurrent task and a more unstable gait (Hausdorff, et al., 2008; Laessoe, et al., 2008; Woollacott & Shumway-Cook, 2002). For example, when completing a concurrent task, older people walk slower, have more variability in stride velocity, and the gaze behaviour of older fallers is considered riskier, with an earlier transfer of gaze away from an obstacle, compared to that of non-fallers (Hollman, Kovash, Kubik, & Linbo, 2007; Plummer-D'Amato, et al., 2012; Timmermans, Roerdink, Janssen, Meskers, & Beek, 2018; Yamada, et al., 2011). The ability to perform concurrent tasks whilst walking has important real-world implications which have also been demonstrated experimentally. For example, when completing concurrent tasks, older people are less likely to safely cross a pedestrian crossing compared to young people (Eggenberger, Tomovic, Münzer, & de Bruin, 2017). We therefore would expect greater difficulty when negotiating more challenging environments when a concurrent task is being performed. However, studies using cognitive load tasks in young people have shown wide-ranging results. For example, gaze fixations toward the floor increase under more cognitively demanding environmental conditions (low lighting, rougher surfaces), when participants complete a concurrent task that requires a timed response (Fotios, Uttley, Cheal, & Hara, 2015). Furthermore, Beurskens and Bock (2013) showed that age-related dual-task costs on step duration and shank angles were greater when walking in more complex environments (obstacles or narrow paths). In contrast, Forte, et al. (2019) found no additional effect on gait stability of completing a concurrent memory task whilst walking over a more complex surface relative to a flat surface. Forte, et al. (2019) suggested that the difficulty of walking over the complex surface may have increased gait instability to a ceiling level such that no extra effect of the secondary task could be detected.

5.2.3 Research aims

In summary, it is well established that reduced cognitive ability has a detrimental effect on the gait stability of older people (as reviewed in Amboni, Barone, & Hausdorff, 2013; Parihar, Mahoney, & Verghese, 2013). Similarly, loss of peripheral vision, particularly the lower visual field, when walking is associated with an increased fall risk for older people (Black, et al., 2011). However, simulations of single, age-associated deficits (including blocked lower visual field and increased cognitive load) produce inconsistent effects on walking in the young (Beurskens & Bock, 2013; Forte, et al., 2019; Graci, et al., 2010; Marigold & Patla, 2008b; Rietdyk & Drifmeyer, 2009; Thomas, et al., 2020a).

One possible reason for the inconsistencies between the effects on gait for older people with various morbidities and on younger people with simulated morbidities is that the simulation studies have only tested one deficit at a time. As we age, the number of comorbidities increases: 30% of people aged 45-64 have at least two comorbidities, increasing to 65% in those aged 65+ (Barnett, et al., 2012). Therefore, previous research that simulated only one deficit would not emulate the conditions affecting many older walkers. This may help to explain why simulations have produced inconsistent findings.

No study, to the authors' knowledge, has simulated two simultaneous deficits to determine whether this will more accurately model the gait problems observed in older people. We did this in order to try to understand why comorbidities increase the rate of falls in older people (Tinetti & Kumar, 2010). In the present study, we investigated the combination of visual deficits and cognitive decline given the high association between them with age (Anstey, Luszcz, & Sanchez, 2001; Clemons, Rankin, & McBee, 2006; Lin, et al., 2004). Individually, both deficits (blocking the lower visual field and performing a cognitive load task) have often been used to simulate age related conditions. This study extended our previous research to investigate whether simultaneously simulating *two* age-related deficits produced deficits in gait and gaze behaviour similar to those observed for older adults with multiple comorbidities.

5.3 Methodology

5.3.1 Perceptual rating study

We conducted an initial rating study to provide objective measures of the surfaces used for this study. Ten participants (6 male, mean ± SD; age = 28.4 ± 3.1 years; height = 176.6 ± 8.8cm, weight = 72.8 ± 10.8kg) rated their perception of the surface roughness and perceived walking stability of the 20 experimental surfaces using a Likert scale (Likert, 1932) between 1 (smooth / stable) and 10 (rough / unstable). The perceptual rating study followed the same procedure as that of Thomas, et al. (2020c). The 20 surfaces were located in the University of Liverpool campus, and represent a range of surface types typical of an urban environment (see **Figure 1**). Each surface was rated three times: for roughness and then for perceived stability from vision alone, and finally for perceived stability again after the participants had walked on the surface. All three measures have been shown to be highly correlated with surface complexity based on physical and behavioural measures (Thomas, et al., 2020c). In the present study, the three perceptual ratings were highly correlated (r = 0.86 roughness and perceived stability before; r = 0.85 roughness and perceived stability after; r = 0.97 perceived stability before and perceived stability after) and scores were therefore averaged into a single surface complexity metric. This metric was used to rank surfaces by complexity, see **Figure 1**.

Figure 1: Images showing the 20 surfaces (S1 – S20) used for this study. Surfaces are ordered by the average rating of surface complexity produced from the perceptual rating study from S1 = least complex to S20 = most complex. Surfaces were rated using a scale from 1 (smooth / stable) to 10 (rough / unstable). Average (±SD) perceptual ratings are shown for each surface. Further details about the surfaces are given in the supplementary material (5.7.1).

5.3.2 Participants

Twenty participants (9 male, mean ± SD; age = 27.7 ± 3.3 years; height = 173.7 ± 8.8cm, weight = 71.2 ± 9.6kg) were tested across eight counterbalancing conditions (see supplementary material 5.7.2 for details). Nine of these participants had already completed the perceptual rating study. No participant required glasses for walking or had any known impairment or injury which might affect their gait or vision. Unfortunately, as is commonplace when collecting data outside the laboratory, technical and environmental factors meant that some data was missing for some measures. See the supplementary materials for details (5.7.3).

5.3.3 Data collection

The University of Liverpool's Ethics Committee granted approval for the study in May 2019 (REF: 4803). Gaze and gait behavioural metrics were assessed during the study. The gaze measurements were head pitch angle, eye angle and the duration and number of fixations. The gait measurements were gait speed and walking smoothness (as measured by anteroposterior harmonic ratios). Eye angles were calculated using eye movements recorded in the vertical direction using a Pupil Labs eye-tracker (Kassner, Patera, & Bulling, 2014) recording pupil movements at 30Hz and a world view at 60Hz. Calibration of the eye-tracker was completed prior to data collection. We also recorded the number and duration of fixations. Fixations were recorded as stabilised eye movement for a minimum of 100 milliseconds following Marigold and Patla (2007); Patla and Vickers (1997, 2003). To enhance the performance of the eye tracker's infrared cameras in sunlight, participants wore an infrared-blocking face shield following Matthis, et al. (2018). Three Delsys TRIGNO™ Inertial Measurement Unit sensors (IMUs) (Boston, MA, USA), were used to record inertial data (148Hz). The IMUs were positioned on the face shield, on the lower back and on the right ankle. The face shield IMU was attached close to the participant's forehead and was used to calculate head pitch angle from the gyroscopic data. Previous research has found differences in head movement when wearing headgear (McKnight & McKnight, 1995). We found that head pitch angle seemed to lower by around 4° due to wearing the face shield, see supplementary material (5.7.4) but note that the face shield was worn in all conditions. Gait speed was calculated from accelerometric data and gait events calculated from the ankle IMU following Li, Young, Naing, and Donelan (2010). Walking smoothness (from anteroposterior harmonic ratios) was calculated from accelerometric data collected from the lower back IMU following Bellanca, Lowry, VanSwearingen, Brach, and Redfern (2013). Harmonic ratios were calculated within a single stride (adjacent gait events), with higher ratios interpreted as a more symmetric, and thus smoother, gait.

We also collected surface electromyography (sEMG) data, using two additional sensors placed on the *Tibialis Anterior* muscle and medial head of the *Gastrocnemius* muscle on the left leg, to calculate leg muscle coactivation whilst walking. However, one of the sensors failed to record properly due to insufficient battery life throughout the experiment and we were unable to analyse this data.

We simulated two intrinsic deficits - blocking the lower visual field and performing a cognitive load task. In order to block the lower visual field, similar to previous research (Rietdyk & Drifmeyer, 2009; Thomas, et al., 2020a), participants wore basketball goggle. These goggles blocked at least the lowest 20° of the visual field (see Thomas, et al., 2020a).

For the cognitive load task, participants pressed a button on a hand-held device as soon as they detected a vibration. This task was similar to that used by Fotios, et al. (2015) who also assessed behavioural changes to gait whilst walking outside. The hand-held device consisted of an Arduino microcontroller which generated the vibration, a DELSYS Trigno Trigger adapter (Boston, MA, USA), which recorded the response time, and a portable power bank. These components were housed in a small, plastic container that could easily be held in one hand. Vibrations occurred randomly between 1 and 3 seconds after the offset of the previous vibration and participants were told to respond rapidly to this task. Participants held the device in their right hand and were advised to rest their thumb on the response button between vibrations. The vibration stopped as soon as they responded or after 5 seconds of continuous vibration, whichever occurred first. Participants were reminded throughout the study to prioritise the cognitive load task to try to restrict any costs from performing the task to gaze and gait behaviours. Participants practised doing the cognitive load task whilst walking indoors before starting the study. **Figure 2** shows an example of the experimental set-up.

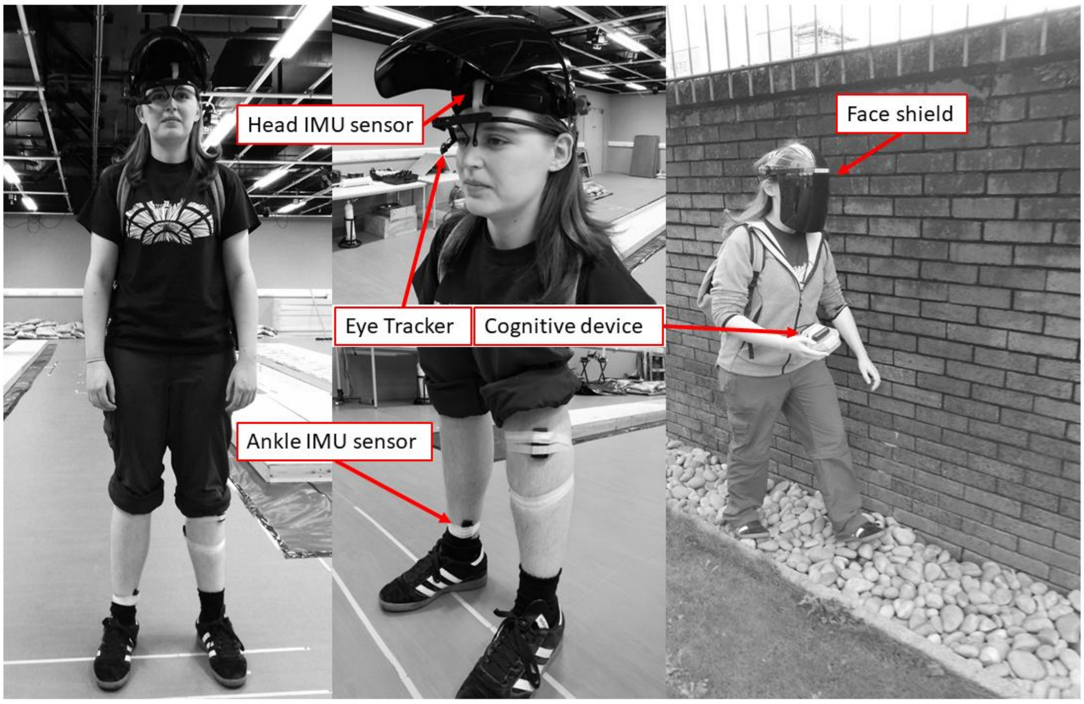


Figure 2: Images showing a participant wearing the face shield (used to enhance performance of the eye tracker's infrared cameras by blocking infrared light), head IMU (used to calculate head pitch angle), eye tracker (used to record eye movements), ankle IMU (used to record inertial data) and the hand-held cognitive load device (used to generate a vibration and record reaction times). Participants also wore an IMU on their lower back (not shown).

5.3.4 Protocol

Participants walked four times across each of twenty surfaces (S1 – S20) located across the University of Liverpool campus (see **Figure 1**). Surface descriptions, the order surfaces were walked upon during data collection and surface lengths are given in the supplementary material (5.7.1). Participants walked on the surfaces in four conditions that comprised every combination of two vision and two cognitive conditions. The vision conditions consisted of either normal, full vision (V+)

or blocked lower visual field (V-). The cognitive conditions consisted of either full cognitive capacity being available to control and monitor their walking (normal walking conditions) (C+) or a reduced cognitive capacity due to performing a concurrent, cognitive load, speeded button press task (C-). The four conditions were thus: full vision and full cognitive capacity (V+C+), full vision and cognitive load task (V+C-), blocked lower visual field and full cognitive capacity (V-C+), and blocked lower visual field and cognitive load task (V-C-).

The two full vision (V+) conditions, and the two blocked lower visual field (V-) conditions were always paired (i.e. completed one immediately after another on each surface) so that the basketball goggles did not have to be removed between paired walks, minimising disruptions to the eye tracker. Participants walked across all twenty surfaces completing one pair of conditions before taking a short break (approximately 5 minutes) and then completing the remaining pair of conditions. The surfaces were initially completed in a fixed order from A to T. After the short break the surfaces were completed again but in the reverse order (due to the experimental set-up), from T to A (see supplementary material 5.7.1). For example, a participant might complete the V+C- then V+C+ conditions for surface A, then for surface B, and so on to surface T, take a break, and then complete the V-C- then V-C+ conditions for surface T, then for surface S, and so on to surface A. The order of conditions within each pair was counterbalanced across participants, as was the assignment of which pair of conditions was completed first (see supplementary material 5.7.2 for the eight possible combinations). Counterbalancing was done to minimise the impact of fatigue on the results. Furthermore, no significant effects were found for gait speed or reaction time (for C- conditions) between the first (A to T surface order) and second (T to A surface order) pair of conditions.

For each surface trial, participants started by looking straight ahead whilst standing still in front of each surface for three seconds, then they walked at a self-determined, comfortable speed across the surface length. At the end of the surface, participants again looked straight ahead whilst standing still for a further three seconds. Participants could move their eyes and head as normal whilst walking and were only told to look straight ahead whilst standing still at the start and end of each surface. For C- trials, participants began using the cognitive device for a minimum of 30 seconds before the surface trial. We tried to ensure that participants completed the study under comparable conditions by avoiding gross changes in extrinsic factors such as weather, lighting, surface friction, time of day and attentional distractions. The total study duration (including debriefing, sensor placements, calibrations, indoor practice trials and the experimental trials themselves) for each participant was approximately 180 minutes of which over 120 minutes was data collection.

5.3.5 Analysis

We analysed gaze and gait measures for each of the four walking conditions. Data from the first and last two steps of walking were excluded from the analysis to ensure that the impact of starting and stopping did not influence the results. Gait measures comprised the mean gait speed and mean walking smoothness as measured by anteroposterior harmonic ratios for each surface. Head pitch angle was calculated using the gyroscopic data recorded from the head IMU, noise reduced using a 10Hz low pass, fourth-order Butterworth filter. Head pitch angles were calculated using numerical integration of the gyroscopic data (collected as °/s). Following Takeda, et al. (2014), signal drift was removed using the periods when the participant remained stationary for three seconds at the beginning and end of each trial. These periods were also used to define a head pitch angle of 0°, calculated from the average head position following Thomas, et al. (2020b). An eye angle of 0° was defined from the eye calibration completed prior to the study, when participants fixated a target set at their eye height. Eye movements away from 0° were converted into eye angles, with negative eye angles defined as downward eye movements. Eye angles outside the normal range expected for V+ (+40 to -70°) and V- (+40 to -50°) conditions were excluded from the analysis based on previous findings (Lee, Kim, Shin, Hwang, & Lim, 2019; Thomas, et al., 2020a). We also calculated mean relative frequency distributions for eye and head pitch angles. Here, for each surface, the angles recorded were separated into bins of 5° following Foulsham, Walker, and Kingstone (2011).

To assess time-locked gaze responses to performance on the cognitive load task (the V+C- and V-C- conditions), we compared gaze in a baseline period before the vibration to gaze during the period that a response was being prepared to the vibration. To do this we calculated average eye and head pitch angle changes across 100 ms intervals from -500ms to +500ms relative to the vibration onset. Mean reaction times were 0.57s (± 0.04 SE) across different surfaces and V+ and V- conditions. Cognitive load is likely to be at its largest during this period of response preparation.

We also calculated the multiple deficit cost on the cognitive load task response times, i.e. the extra burden to responding to the vibration due to lower vision also being blocked. This was calculated using the following equation:

$$\begin{aligned}&Multiple\ deficit\ cost\ (\%)\\&= 100\ \times \frac{multiple\ deficit\ \mathrm{V-C}-perfomance\ -single\ deficit\ \mathrm{V+C}-performance}{single\ deficit\ \mathrm{V+C}-performance}\end{aligned}$$

We ran mixed-effects models for each of the gaze and gait measures, with surface complexity ratings (see **Figure 1**), vision condition (V+, full vision or V-, blocked lower visual field) and cognition condition (C+, full cognition or C-, cognitive load task) as fixed effects and participants as random effects. Significant differences were determined as those with a *p* value of less than 0.05.

Finally, we conducted Pearson's correlations on the mean z-scores of the different measures for each surface. The z-scores for the number of fixations were multiplied by -1 so that, for all measures, higher z-scores were always associated with more stable walking. Large correlations ($r > 0.5$, as determined by Cohen (2013)) are shown in bold for each correlation table. A conservative alpha level of 0.001 was used for correlations, calculated using the Bonferroni correction.

5.4 Results

5.4.1 Head pitch and eye angles

Mean head pitch and eye angles for the four conditions are shown in **Figures 3A** and **3B** respectively. The mean frequency distribution for head pitch and eye angles for all four conditions are shown in the supplementary material (5.7.5).

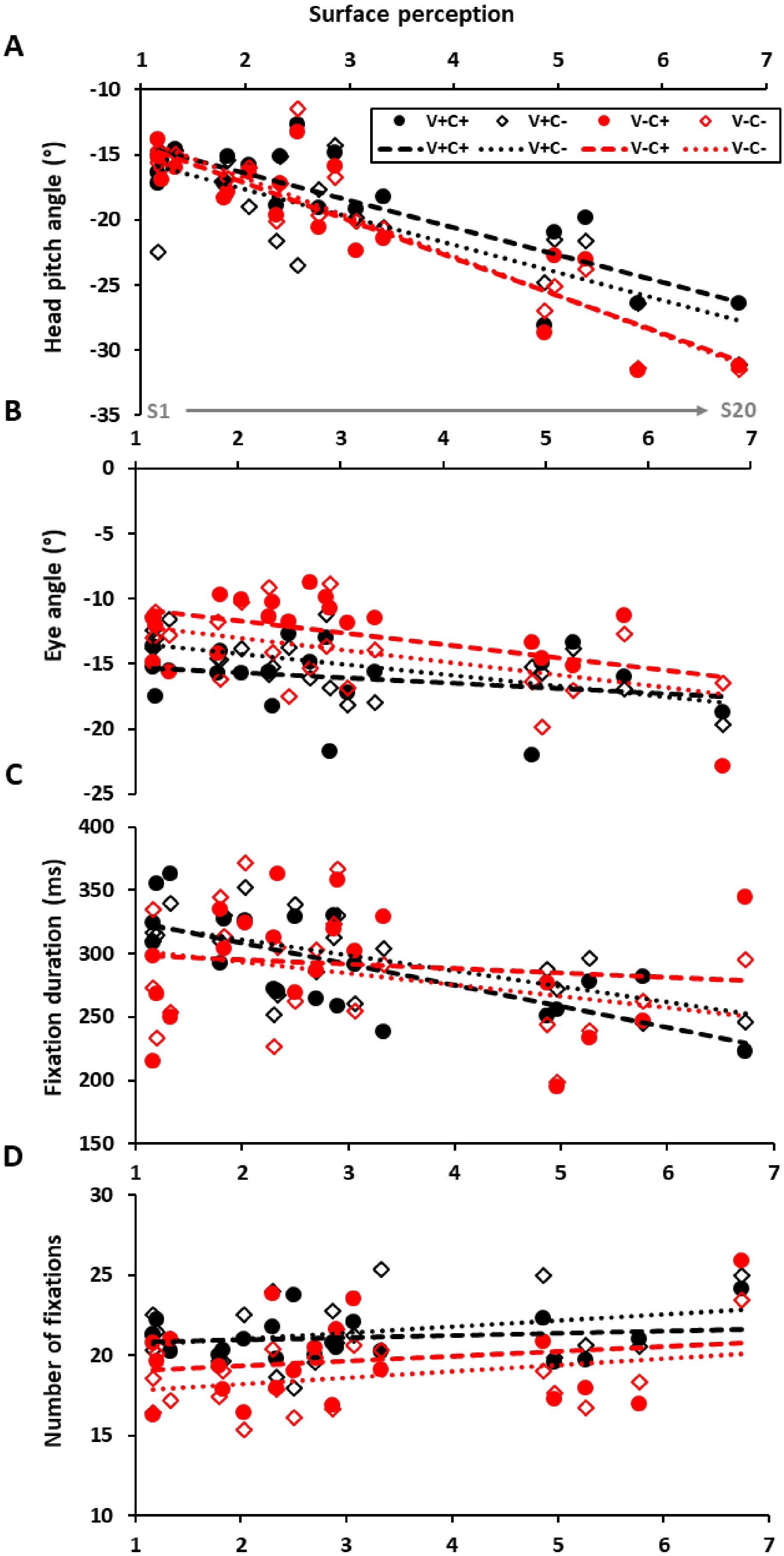
Surface complexity and vision condition both had a significant effect on head angle, $F(14,691) = 47.63, p < 0.001$ and $F(1,691) = 13.31, p < 0.001$ respectively. The head lowered as surface complexity increased and was lower under V- (M ± SE = -20.0° ± 0.6) compared to V+ (M ± SE = -19.1° ± 0.7) conditions. There was also a significant interaction between surface complexity and vision, $F(14, 691) = 1.97, p = 0.018$. A t-test comparing the V+ and V- conditions showed no significant difference between regression intercepts *(t(3) = -1.56, p = 0.121)*, however, there was a significant difference between regression slopes *(t(3) = -5.59, p < 0.001)*, with the head lowering more under V- than V+ conditions as surface complexity increased. For the least complex surfaces, head pitch angle for both visual conditions were similar (~-15°) whereas for the most complex surfaces, head pitch angle was ~5° lower for the V- (~-30) compared to the V+ (~-25°) conditions. There were no other significant main effects or interactions.

Vision condition had a significant effect on eye angle, F*(1,652) = 7.83, p = 0.005*, with a lower eye angle under V+ (M ± SE = -15.6 ± 0.7) compared to V- (M ± SE = -13.2 ± 0.7) conditions. There were no significant main effects of surface complexity or cognition and no significant interactions.

5.4.2 Duration and number of eye fixations

The mean duration and number of fixations for the four conditions are shown in **Figures 3C** and **3D** respectively. Surface complexity had a significant effect on fixation duration, *F(14,652) = 2.83, p < 0.001*, with shorter fixations as surface complexity increased. There was also a significant interaction between surface perception and vision, *F(14,652) = 2.24, p = 0.006*. A t-test comparing the V+ and V- conditions showed no significant difference between regression slopes (*t(3) = 1.32, p = 0.187)*, but a significant difference between regression intercepts *(t(3) = -3.35, p = 0.001)*. Fixations were shorter under V- than V+ conditions regardless of surface complexity. There were no main effects of vision or cognition and no other significant interactions. Both surface complexity and vision had a significant effect on number of fixations, *F(14,652) = 4.17, p < 0.010* and F(1,652) = 32.02, *p < 0.001* respectively. There were more fixation as surface complexity increased and more fixations for V+

($M \pm SE = 21.3 \pm 0.3$) compared to V- ($M \pm SE = 19.2 \pm 0.4$) conditions. There were no significant main effects of cognition and no significant interactions.



Surface perception
A
Head pitch angle (°)
V+C+
V+C-
V-C+
V-C-
S1
S20
B
Eye angle (°)
C
Fixation duration (ms)
D
Number of fixations

Figure 3: Mean (**A**) head pitch angles, (**B**) eye angles, (**C**) fixation duration and (**D**) number of fixations for the V+C+ (black, filled circles), V+C- (black, outlined diamonds), V-C+ (red, filled circles) and V-C- (red, outlined diamonds) conditions for each of the 20 surfaces. Surfaces were rated from the easiest and simplest to traverse (S1) to the hardest and most complex (S20) using a surface perception scale from 1 (smooth / stable) to 10 (rough / unstable). Dotted lines represent the regression lines for each condition.

5.4.3 Gait speed

Mean gait speeds for the four conditions are shown in **Figure 4A**. Both surface complexity and cognitive condition had significant effects, $F(14,1521) = 73.63, p < 0.001$ and $F(1,1521) = 5.24, p = 0.022$ respectively. Gait slowed as surface complexity increased and was slower under C- (M ± SE = 1.38 m/s ± 0.01) compared to C+ (M ± SE = 1.36 m/s ± 0.01) conditions. There were no main effects of vision condition and no significant interactions.

5.4.4 Walking smoothness as measured by mean harmonic ratios

Mean anteroposterior harmonic ratio for the four conditions are shown in **Figure 4B**. Both surface complexity and vision condition had a significant effect on harmonic ratios, $F(14,1521) = 108.73, p < 0.001$ and $F(1,1521) = 10.84, p = 0.001$ respectively. Harmonic ratios were reduced as surface complexity increased and were reduced for V- (M ± SE = 3.03 ± 0.04) compared to V+ (M ± SE = 3.12 ± 0.03) conditions. There were no main effects of cognitive condition and no significant interactions.

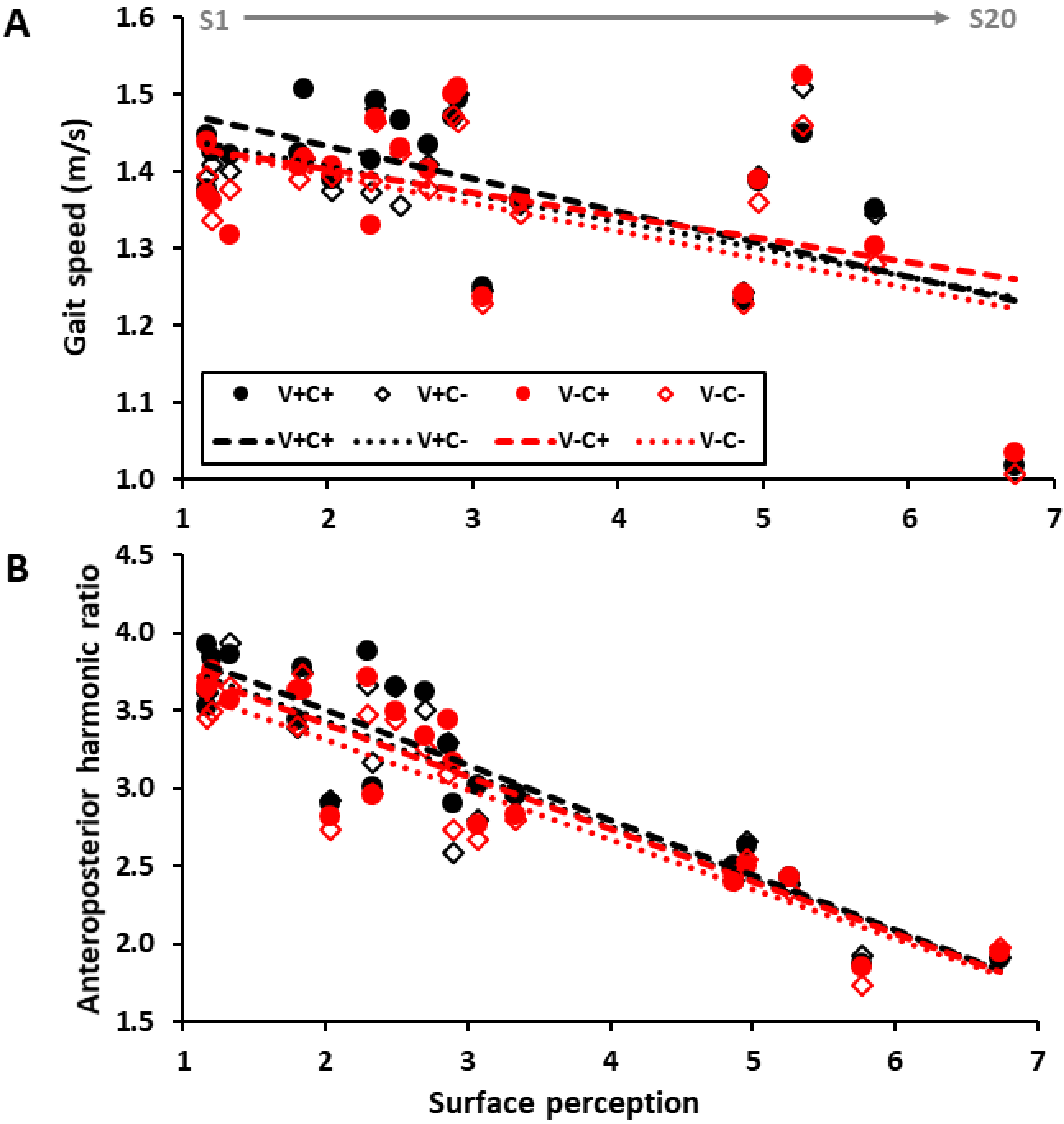


Figure 4: Mean (**A**) gait speed (metres/second) and (**B**) anteroposterior harmonic ratios used to measure walking smoothness for V+C+ (black, filled circles), V+C- (black, outlined diamonds), V-C+ (red, filled circles) and V-C- (red, outlined diamonds) conditions for each of the 20 surfaces. Surfaces were rated from the easiest and simplest to traverse (S1) to the hardest and most complex (S20) using a surface perception scale from 1 (smooth / stable) to 10 (rough / unstable). Dotted lines represent the regression lines for each condition.

5.4.5 Cognitive load task reaction times

Reaction times were calculated for the button press response relative to the onset of the vibrations. Only one vibration was missed. On average, participants responded to five vibrations per surface (M ±SE = 5.1 ±0.4) for both the V+C- and V-C- conditions. Mean number of vibrations per surface and condition are shown in the supplementary material (Table 5.7.6). Mean reaction times to the onset of the vibrations and multiple deficit reaction time costs are shown in **Figure 5A and 5B** respectively. A mixed-effects model found no main effects of surface complexity or vision condition and no significant interaction. The lack of an effect of surface complexity indicated that people did not slow their responses to the cognitive load task when they walked over the more complex surfaces. This suggests that participants followed their instructions and prioritised the cognitive load task.

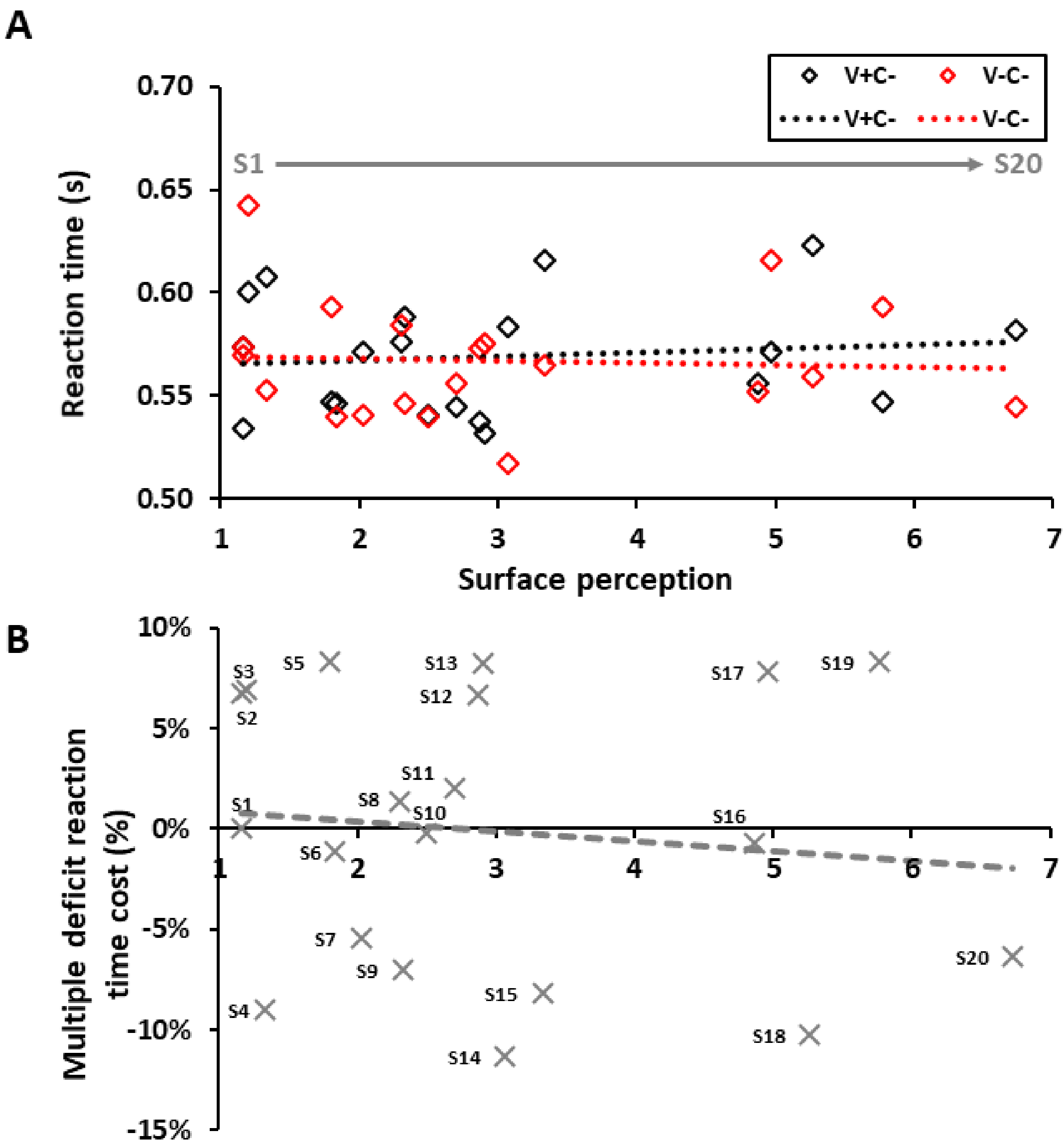


Figure 5: Mean (A) reaction times (seconds) for V+C- (black, outlined diamonds) and V-C- (red, outlined diamonds) conditions and (B) multiple deficit reaction time cost (i.e. enhanced cost for V-C- relative to V+C- conditions, calculated as: 100 x (*reaction times V-C- conditions* - *reaction times V+C- conditions*) ÷ *reaction times V+C- conditions*) for each of the 20 surfaces. Surfaces were rated from the easiest and simplest to traverse (S1) to the hardest and most complex (S20) using a surface perception scale from 1 (smooth / stable) to 10 (rough / unstable). Dotted lines represent the regression lines for each condition.

5.4.6 Cognitive load effect on head pitch and eye angles

We assessed whether there were any short-term effects on gaze due to responding to the vibration onset. Mean head pitch and eye angles, averaged across all 20 surfaces, were calculated at five 100 millisecond intervals prior to and subsequent to the vibration onset. The onset of the vibration did not have a significant effect on either head pitch or eye angles and there were no significant differences between V+C- and V-C- conditions (see supplementary material, 5.7.7). This suggests that neither eye or head movement changed due to responding to the cognitive load task.

5.4.7 Pearson’s correlations

Pearson’s correlations were conducted on the mean z-scores (see supplementary material, 5.7.8) for the four conditions for each of the behavioural measures in turn (see Table 5.7.8.1) and for the different behavioural measures for each of the four conditions in turn (see Tables 5.7.8.2 - 5.7.8.5). Head pitch angle, gait speed and walking smoothness, as measured by harmonic ratios, were all highly correlated across the vision and cognitive load conditions relative to correlations for eye angle, fixation durations and number of fixations. There were no significant correlations between eye angle and any other behavioural measure for a given vision and cognitive load condition. This suggests that eye movements behaved less consistently than movements of other parts of the body.

5.4.8 Combined behavioural z-scores

We conducted a mixed-effects model on the z-scores for a combination of behavioural measures for each surface and condition. Eye angle, fixation duration and number of eye fixations were excluded from this analysis given that they correlated poorly with other measures (see supplementary material, 5.7.8). An average z-score was calculated for the remaining three behavioural measures (head pitch angle, gait speed and walking smoothness as measured by harmonic ratios) to check if this combined measure provided a more sensitive measure to the influence of the concurrent task or blocking the lower visual field. This was not found to be the case, see supplementary material (5.7.9). Surface complexity and vision condition had a significant effect on the combined z-scores, with lower z-scores as surface complexity increased and under V- conditions. There was no effect of cognitive conditions and no significant interactions.

5.5 Discussion

The aim of this study was to address how simulating two age-related deficits, cognitive decline and lower visual field loss, affected gaze and gait behaviour across a range of outdoor surfaces of different complexities. Contrary to our predictions, combining extrinsic and intrinsic deficits did not, in general, enhance their individual effects and there were few interactions between the effects of surface complexity, vision and cognitive load. This contrasts to studies with older people that have shown an increased fall risk arising from an increased number of comorbidities, particularly in more complex environments (Bao, et al., 2019; Sotimehin, et al., 2018; Vu, Finch, & Day, 2011). Our present results suggest that simulations of multiple age-related deficits associated with an increased fall risk may not provide an informative model for how such conditions affect older people. Thus, we suggest that future research investigating gait stability should, where possible, directly study the affected population group rather than simulating conditions in young, healthy participants.

Individually surface complexity and the two intrinsic factors did alter behaviour:

5.5.1 Surface complexity

Increased surface complexity had a significant effect on all our behavioural measures except for eye angle. The surfaces tested here spanned a wide range of surfaces typically found in outdoor environments. More complex surfaces were associated with lower head pitch angles, more and briefer fixations, and slower, more asymmetric gait, supporting findings from previous studies ('t Hart & Einhauser, 2012; Matthis, et al., 2018; Thomas, et al., 2020a, 2020c). These results, are consistent with the finding that both the young and the old (who are more likely to also have intrinsic factors affecting their mobility), generally fall due to extrinsic rather than intrinsic factors (Berg & Cassells, 1990; Bueno-Cavanillas, Padilla-Ruiz, Jimenez-Moleon, Peinado-Alonso, & Galvez-Vargas, 2000).

5.5.2 Lower visual field loss

Blocking the lower visual field also caused behavioural change. Not surprisingly, blocking the lower visual field altered gaze, with the head lowering and eye angle rising as well as the number of fixations reducing. It also reduced walking smoothness as measured by anteroposterior harmonic ratios. However, the behavioural changes due to blocking vision conditions were less than those caused from increasing surface complexity. For example, anteroposterior harmonic ratios were decreased by 0.14 in V- conditions compared to V+ conditions, whereas harmonic ratios decreased by 1.72 from the smoothest to most complex surface. Similarly, head pitch only lowered by ~1° with blocked vision compared to ~12° for the most complex surface.

5.5.3 Cognitive decline

Inducing an increased cognitive load in the form of a speeded vibration detection task had little effect on any of the gaze or gait behaviours assessed. This suggests that young people are robust to challenges to their walking from an increased cognitive load when walking outside. This was the case even when the cognitive load was combined with reduced visual input or high surface complexity. Forte, et al. (2019) suggested for their study that more challenging extrinsic factors may introduce a ceiling effect and thus effects of a concurrent task may not be detected. This could explain our findings for the more complex surfaces in the present study. However, unlike Forte, et al. (2019), we did not find any effect of the concurrent task on behaviour even for the easiest, least complex surfaces. The lack of an effect may be because participants completed a simple response task. We chose a simple, speeded button press task so that performance could be easily monitored when walking and as this type of cognitive load task has been used previously when walking outdoors (Fotios, et al., 2015). However, more cognitively challenging tasks are known to be associated with greater behavioural change (Forte, et al., 2019; Muir, et al., 2012). Numerical tasks (e.g. counting backwards in set intervals) are a more common means of applying a cognitive load, however, such tasks may influence participant's rhythmicity rather than their attention (Beauchet, Dubost, Aminian, Gonthier, & Kressig, 2005). As such, future studies in the young, may need to use more powerful simulations (e.g. using more challenging tasks) to elicit a more substantial behavioural cost.

Another explanation as to why the current study showed few behavioural changes under cognitive load conditions may be due to most previous studies testing under laboratory conditions (e.g. Hollman, et al., 2007; Plummer-D'Amato, et al., 2012; Yamada, et al., 2011). Our study was conducted outside, in relatively uncontrolled conditions. Here, the baseline cognitive load was likely much higher than in a laboratory, with many and varying visual and auditory distractions from pedestrians and traffic as well as from walking at many different locations. This background distraction may have made it difficult to detect the addition of a simple cognitive load task on behaviour. The difficulty for future studies is to balance control of experimental factors but also to emulate real world conditions. Testing outside, with high uncontrolled variability, may mask behavioural changes arising from an increased cognitive load task, as shown here. However, conclusions from studies in laboratories may not generalise to conditions found in the real world where most falls occur. For example, Hillel, et al. (2019) showed that the spatiotemporal parameters of gait in older people in daily living were more like those obtained when walking in the laboratory whilst doing a concurrent task rather than when only walking in the laboratory.

One limitation of the study, was that participants only walked across each surface once in each of the four conditions. This was due to the total duration of the study (approximately 180 minutes) and the limited battery life for the IMU sensors used in the study. However, note that our behavioural measures were averaged across several steps to minimise the effect of outliers. For this study, we focused on assessing average behaviour. Future research could assess coupling of gaze and gait behaviours similar to the analyses reported recently by (Matthis, et al., 2018). Another limitation of the study was that we had two separate, serious equipment failures so our data set was incomplete making it difficult to draw strong conclusions based on the results. Future advancements in wearable technology storage, hardware and software should prevent this from happening in future studies.

5.6 Conclusion

The present study furthers our understanding of how simulated, age-related deficits affect gait and gaze behaviour whilst walking across the types of surfaces that are typically encountered outside. This study is the first to assess how two intrinsic factors, namely lower visual field loss and increased cognitive load, affect behaviour both individually and in combination. Our young participants seemed to be quite robust to a blocked lower visual field and to performing a concurrent, simple reaction time task. Our finding contrasts with the well-documented deficits found for older people with cognitive decline when walking outside. We therefore conclude that we should be cautious about drawing conclusions based on simulated deficits. Instead, future studies should focus on trying to understand fall risks in groups that are directly affected by these deficits (i.e. those with dementia, glaucoma, etc.), rather than trying to simulate the deficits in the young.

5.7 Supplementary Materials

5.7.1 Order of completion

Figure 5.7.1 & **Table 5.7.1** show the order of completion of the different surfaces. Table 5.7.1 also gives surface descriptions and surface lengths

Table 5.7.1 Descriptions of the 20 experimental surfaces used in the study together with the order of completion and approximate surface length (to the nearest metre).

Surface	Description	Order of completion (A to T/T to A)	Length (metres)
S1	Flat flagstone paving	E	21
S2	Tarmac pavement	N	22
S3	Flat flagstone slabs	S	21
S4	Brick paving	H	20
S5	Flagstone slabs	C	19
S6	Fine gravel	J	19
S7	Flat grass	M	19
S8	Incline slope	Q	21
S9	Fine gravel	L	18
S10	Ridged paving slabs	G	18
S11	Decline slope	P	21
S12	Setts	A	20
S13	Rough gravel	R	21
S14	Woodchip path	I	22
S15	Uneven dirt path	O	20
S16	Loose pebbles	D	22
S17	Small loose pebbles	K	19
S18	Embedded stones in concrete	T	21
S19	Oblique paved slope	B	19
S20	Loose stones	F	23

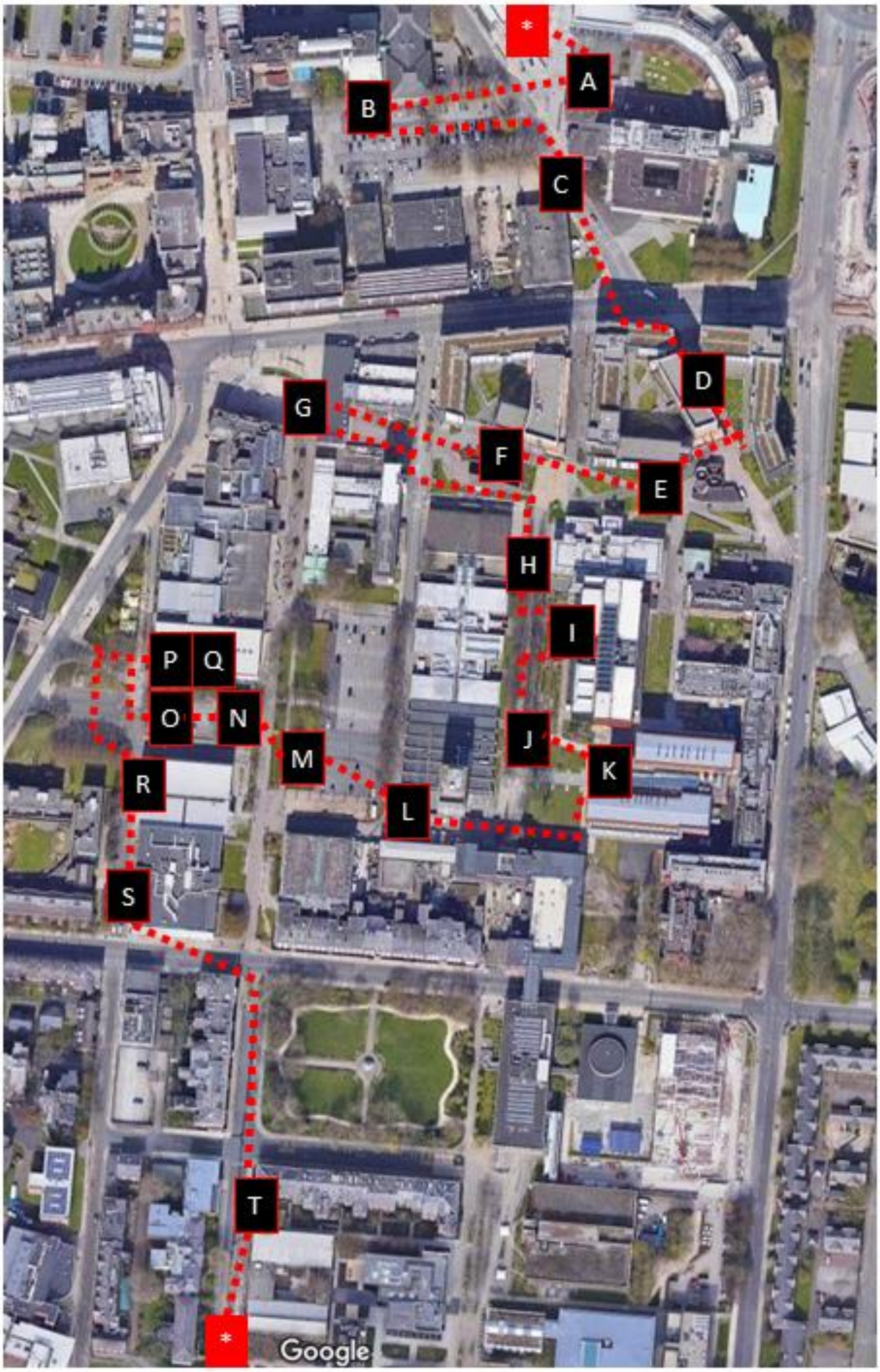


Figure 5.7.1: Order of surface completion (A to T or T to A) shown using a Google Map satellite image of the University of Liverpool campus. The two asterisks denote the laboratories used for the experimental set-up.

5.7.2 Counterbalancing combinations

Table 5.7.2: The eight combinations of conditions that participants could be assigned to. The first pair of conditions were completed successively at each surface in turn for all twenty surfaces. Participants then took a short break before completing the second pair of conditions for the twenty surfaces in the reverse order. Full vision (V+C+ and V+C-) conditions were always paired together, as were blocked lower visual field conditions (V-C+ and V-C-).

First pair	**Second pair**	**Number of participants**
V+C+ & V+C-	V-C+ & V-C-	3
V+C- & V+C+	V-C+ & V-C-	3
V+C- & V+C+	V-C- & V-C+	3
V+C+ & V+C-	V-C- & V-C+	3
V-C+ & V-C-	V+C+ & V+C-	2
V-C+ & V-C-	V+C- & V+C+	2
V-C- & V-C+	V+C- & V+C+	2
V-C- & V-C+	V+C+ & V+C-	2

5.7.3 Missing data

Table 5.7.3: A list of the behavioural measures for which fewer than the total number of participants (n = 20) contributed to the analysis and an explanation of why data was missing

Factors	**Affected participants**	**Reason**

Eye angle, fixation duration and number of fixations	9**	Eye tracker hardware issues
Head pitch angle*	10**	Head IMU software issues
Surface 13*	8	Surface was not available for testing partway through the study

*8 of the 10 participants that walked over surface 13 had erroneous head pitch angle data so this surface was removed from the head pitch angle analysis.

** Of the included participants, less than 2% of eye data and less than 1% of head pitch data was out of the expected range and had to be replaced by the mean for the condition.

5.7.4 Effect of the infrared face shield on head pitch angle

We conducted a validation study to assess the effect of wearing the infrared face shield. A single participant walked five times over an indoor smooth surface and five times over an uneven surface with and without wearing the infrared face shield. The results for the twenty trials are shown in **Figure 5.7.4**. Head pitch angle was around 4° lower whilst wearing the face shield for both the smooth and the uneven surfaces.

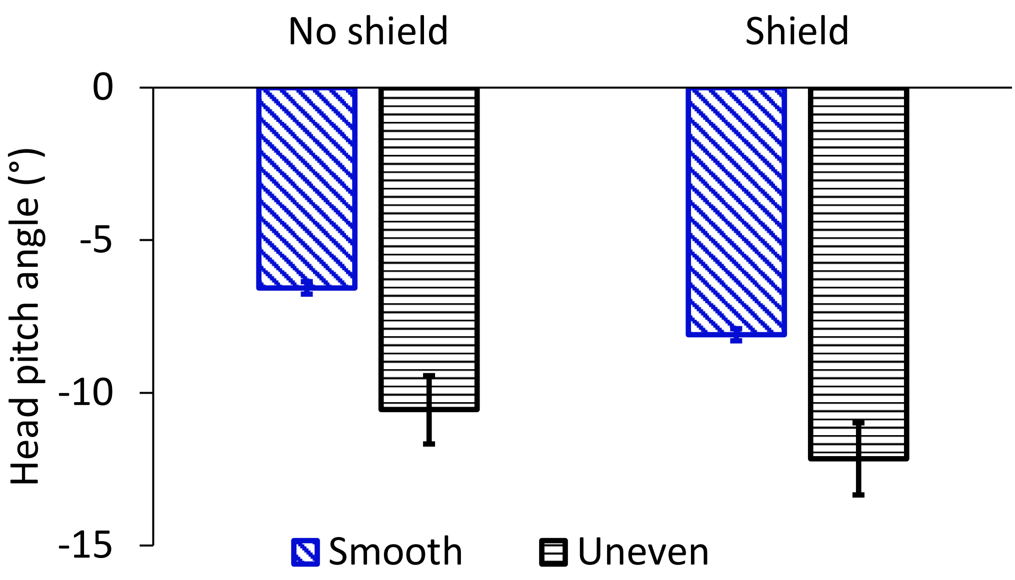


Figure 5.7.4: Mean head pitch angle (degrees) + SE for the smooth and uneven conditions, with and without a face shield.

We had intended to collect data from more participants but testing was interrupted due to the 2020 coronavirus pandemic. As an alternative, we assessed how mean head pitch angle in the present study (when wearing the face shield) compared to that of our previous study (Thomas, et al., 2020a) (when no face shield was worn) for the five surfaces (S4, S6, S17, S18, S19) that were common to both studies. For these five surfaces, head pitch angle was, on average (±SD), 3.2° (±3.86) and 5.1° (±4.61) lower under the full and blocked lower peripheral visual field conditions respectively in the present study when a face shield was worn. Taking the single participant validation study (see **Figure 5.7.4**) with this cross-study comparison, it appears that head pitch angle was somewhat lower (by around 4°) when a face shield was worn.

5.7.5 Relative frequency plot

Figure 5.7.5.1 shows the relative frequency plots for (**A**) eye and (**B**) head pitch angle averaged over all 20 surfaces whilst **Figure 5.7.5.2** and **Figure 5.7.5.3** show relative frequency for each individual surface, in order of surface complexity.

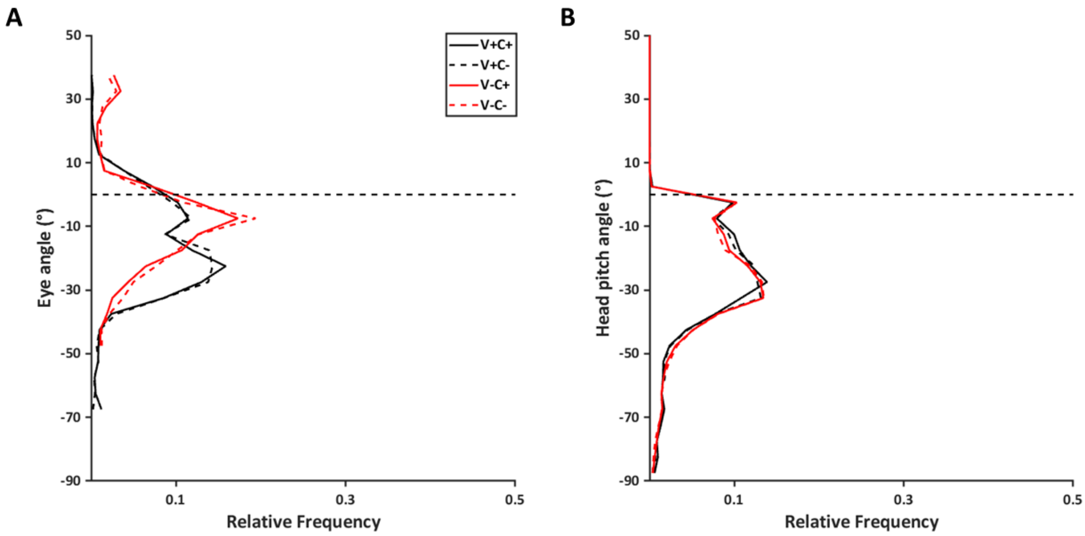


Figure 5.7.5.1: Overall mean relative frequency distributions of eye (**A**) and head pitch (**B**) angle across the 20 surfaces for V+C+ (black, solid line), V+C- (black dashed line), V-C+ (red solid line) and V-C- (red dashed line) conditions. On the y-axis, results are plotted for 5° bins relative to 0° (looking straight ahead). Negative angles correspond to lowering of the eyes (A) or head (B) toward the ground.

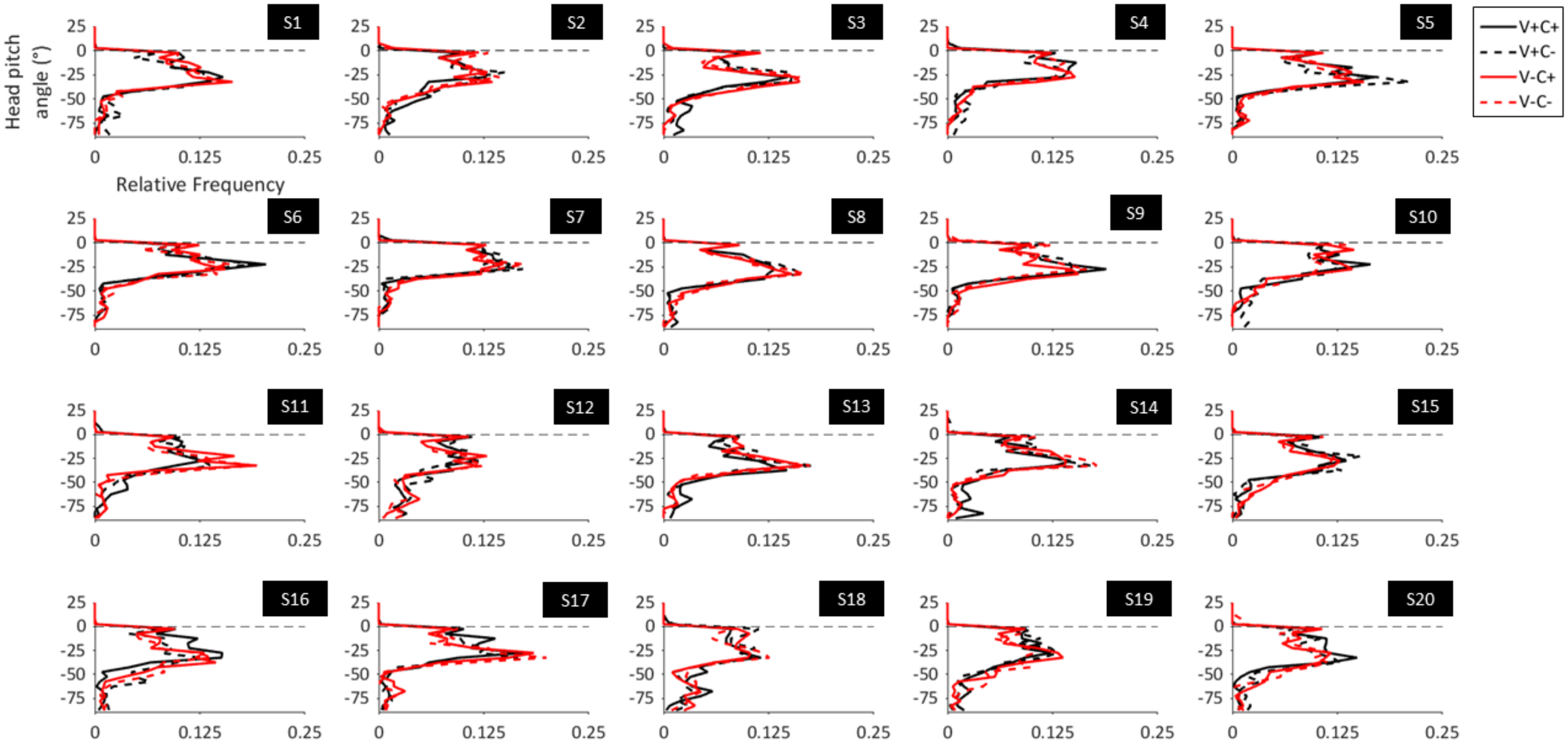


Figure 5.7.5.2: Mean relative frequency distributions of head pitch angle (°) for surfaces S1 (top left) to S20 (bottom right) for V+C+ (black, solid line), V+C- (black dashed line), V-C+ (red solid line) and V-C- (red dashed line) conditions. On the y-axis, results are plotted for 5° bins relative to 0° (looking straight ahead). Negative angles correspond to lowering of the head toward the ground.

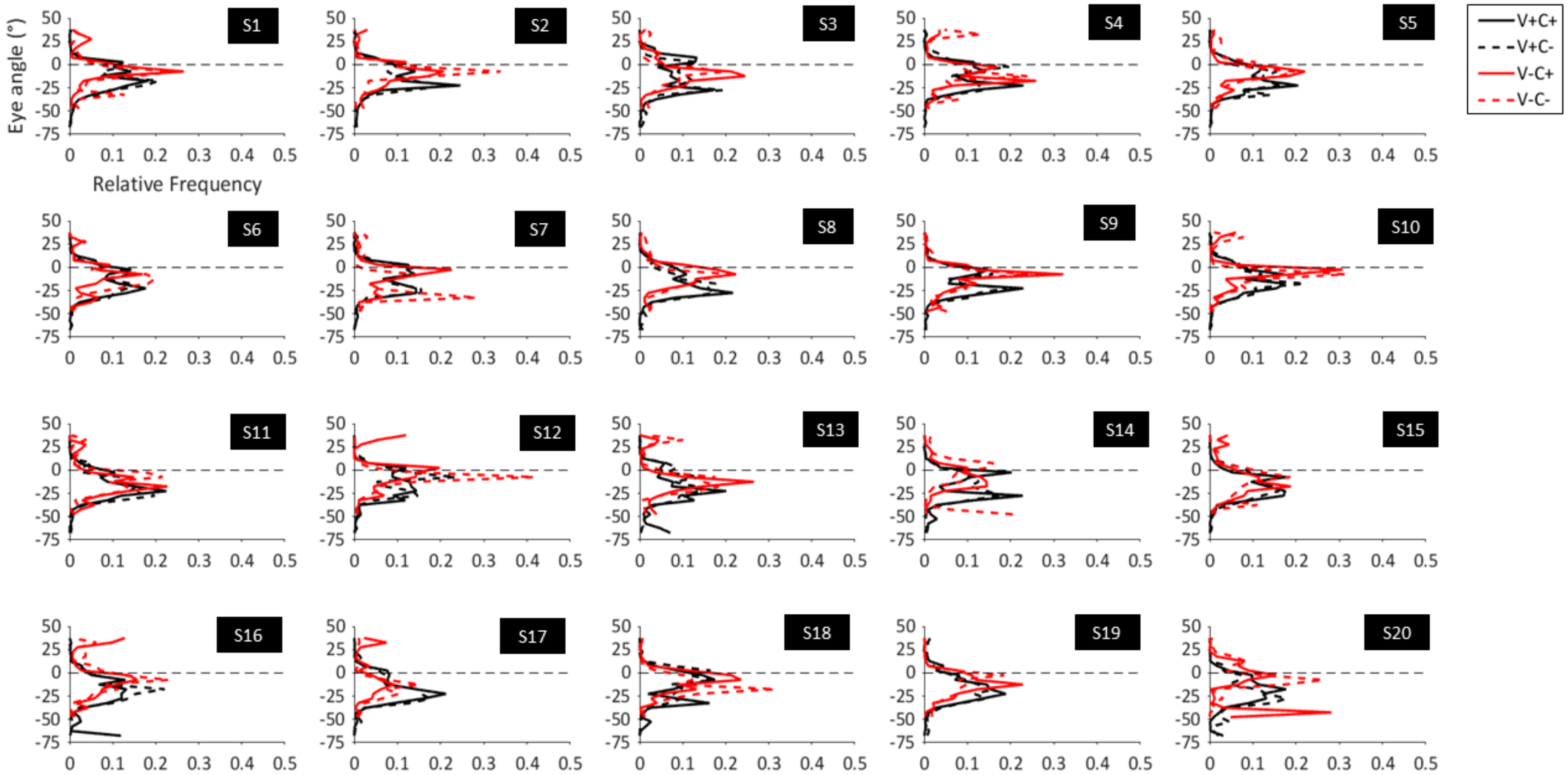


Figure 5.7.5.3: Mean relative frequency distributions of eye angle (°) for surfaces S1 (top left) to S20 (bottom right) for V+C+ (black, solid line), V+C- (black dashed line), V-C+ (red solid line) and V-C- (red dashed line) conditions. On the y-axis, results are plotted for 5° bins relative to 0° (looking straight ahead). Negative angles correspond to lowering of the eyes (A) or head (B) toward the ground.

Table 5.7.6 Mean (±SE) number of vibrations per surface and condition. Note that the surfaces differed in length, see supplementary material (Table 5.7.1), which accounts for some of the variation between surfaces.

	V+C-		**V-C-**	
Surface	Mean	SE	Mean	SE
S1	**5.3**	0.4	**5.2**	0.4
S2	**4.8**	0.3	**5.0**	0.4
S3	**4.9**	0.3	**5.1**	0.4
S4	**4.9**	0.4	**5.2**	0.4
S5	**5.1**	0.3	**5.0**	0.4
S6	**5.3**	0.6	**5.2**	0.6
S7	**4.6**	0.3	**4.5**	0.4
S8	**5.2**	0.4	**5.3**	0.4
S9	**4.6**	0.3	**4.5**	0.3
S10	**4.4**	0.3	**4.9**	0.4
S11	**5.1**	0.4	**5.1**	0.4
S12	**5.3**	0.4	**5.1**	0.4
S13	**4.1**	0.5	**4.6**	0.6
S14	**5.1**	0.3	**5.4**	0.4
S15	**5.2**	0.4	**5.6**	0.5
S16	**5.5**	0.4	**5.6**	0.4
S17	**4.8**	0.3	**4.9**	0.4
S18	**4.8**	0.4	**5.0**	0.4
S19	**5.4**	0.5	**5.0**	0.5
S20	**6.5**	0.5	**6.2**	0.5

5.7.7 Cognitive load effect

Figure 5.7.7 shows mean head pitch angles calculated at 100 millisecond intervals prior to and subsequent to the vibration onset and averaged across surfaces. We conducted a within-subjects ANOVA for the head pitch angle data with two within-subject factors of vision (V+, full vision versus V-, blocked lower visual field) and time (100ms intervals between -500 and +500 relative to vibration onset). Head pitch angle was significantly lower in V- compared to V+ conditions, $F(1,19) = 16.4$, $\eta_p^2 = 0.46$, $p = 0.001$. There was no significant effect of time and no interaction between vision and time. We were unable to run an analogous ANOVA for eye angle data as there was insufficient data within the expected range of angles for these narrow time bins.

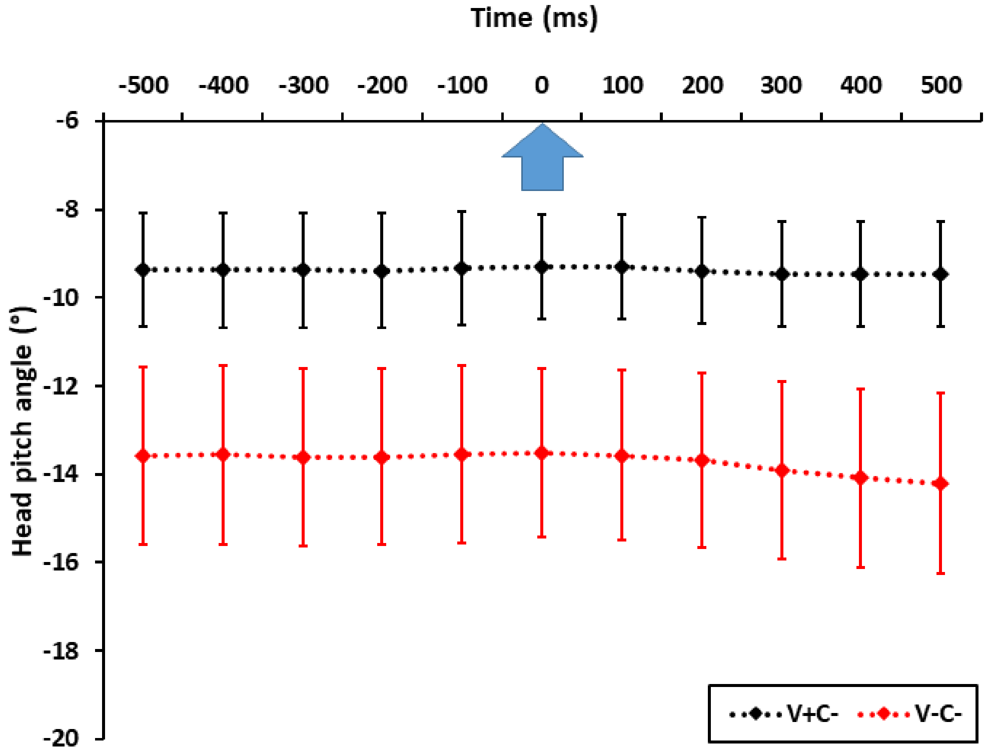


Figure 5.7.7: Mean (±SE) head pitch angle averaged across surfaces (S1-S20), at 100ms intervals from -500ms to +500ms relative to the vibration onset for the cognitive load task (blue arrow) for the V+C- (black, diamonds) and V-C- (red, diamonds) conditions.

5.7.8 Pearson's correlations

Pearson's correlations between mean z-scores across the 20 surfaces for the six gaze and gait behavioural measures. Z-scores were multiplied by -1 for number of fixations so that for all measures higher z-scores were always associated with more stable walking.

Table 5.7.8.1: Pearson's correlations between behavioural measures for the four different conditions (V+C+, V+C-, V-C+, V-C-). * signifies a significant correlation of p *<0.001 (*as determined by the Bonferroni correction) and bold values signify large correlations (r > 0.5) as determined by Cohen (2013).

	Eye angle	Fixation duration	Number of fixations	Head pitch angle	Gait speed	AP harmonic ratio
V+C+ ***x*** V+C-	**0.56**	**0.67**	0.34	**0.90***	**0.93***	**0.97***
V+C+ ***x*** V-C+	0.03	-0.28	**0.57**	**0.75***	**0.84***	**0.95***
V+C+ ***x*** V-C-	-0.41	0.14	0.37	**0.79***	**0.91***	**0.94***
V+C- ***x*** V-C+	-0.07	-0.05	0.28	**0.89***	**0.88***	**0.95***
V+C- ***x*** V-C-	-0.24	**0.52**	0.41	**0.89***	**0.96***	**0.97***
V-C+ ***x*** V-C-	0.41	**0.63**	**0.79***	**0.95***	**0.94***	**0.94***

Table 5.7.8.2: Pearson's correlations between mean z-scores for V+C+ conditions. * signifies a significant correlation of p *<0.001 (*as determined by the Bonferroni

correction) and bold values signify large correlations (r > 0.5) as determined by Cohen (2013).

	Fixation duration	Number of fixations	Head pitch angle	Gait speed	AP harmonic ratio
Eye angle	0.42	0.23	0.42	0.39	0.33
Fixation duration		0.04	**0.74***	**0.52**	**0.59**
Number of fixations			0.29	**0.66**	0.08
Head pitch angle				**0.66**	**0.79***
Gait speed					**0.50**

Table 5.7.8.3: Pearson's correlations between mean z-scores for V+C- conditions. * signifies a significant correlation of $p < 0.001$ (as determined by the Bonferroni correction) and bold values signify large correlations (r > 0.5) as determined by Cohen (2013).

	Fixation duration	Number of fixations	Head pitch angle	Gait speed	AP harmonic ratio
Eye angle	**0.59**	0.19	**0.64**	**0.56**	**0.60**
Fixation duration		0.10	**0.72***	**0.51**	0.46
Number of fixations			0.29	**0.52**	0.20
Head pitch angle				**0.61**	**0.82***
Gait speed					0.38

Table 5.7.8.4: Pearson's correlations between mean z-scores for V-C+ conditions. * signifies a significant correlation of $p < 0.001$ (as determined by the Bonferroni

correction) and bold values signify large correlations (r > 0.5) as determined by Cohen (2013).

	Fixation duration	Number of fixations	Head pitch angle	Gait speed	AP harmonic ratio
Eye angle	-0.22	0.01	-0.12	0.19	0.21
Fixation duration		-0.49	0.23	-0.21	-0.06
Number of fixations			0.11	**0.77***	0.03
Head pitch angle				0.33	**0.72***
Gait speed					0.22

Table 5.7.8.5: Pearson's correlations between mean z-scores for V-C- conditions. * signifies a significant correlation of $p < 0.001$ (as determined by the Bonferroni correction) and bold values signify large correlations (r > 0.5) as determined by Cohen (2013).

	Fixation duration	Number of fixations	Head pitch angle	Gait speed	AP harmonic ratio
Eye angle	-0.17	-0.47	-0.18	-0.06	0.01
Fixation duration		0.04	**0.56**	0.23	0.11
Number of fixations			0.36	**0.65**	0.25
Head pitch angle				0.45	**0.72***
Gait speed					0.24

5.7.9 Combined behavioural z-scores

We calculated combined behavioural z-scores averaged across head pitch angle, gait speed and walking smoothness as measured by harmonic ratios, for each surface and condition. As head angles were excluded for surface s13 (see supplementary material, 5.7.3), z-scores for that surface were calculated across gait speed and walking smoothness only. Eye angle, fixation duration and number of fixations were excluded from this combined z-score due to weak correlations with other measures (see supplementary material, 5.7.8). The combined z-scores for the different surfaces are shown in **Figure 5.7.9**. Surface complexity and vision had a significant effect, $F(14,20) = 61.91, p < 0.001$ and $F(1,20) = 7.34, p = 0.014$ respectively. Z-scores were lower as surface complexity increased and were lower under V- (M ± SE = 0.16 ± 0.19) compared to V+ (M ± SE = 0.10° ± 0.20) conditions. There were no main effects of cognitive load condition and no significant interactions.

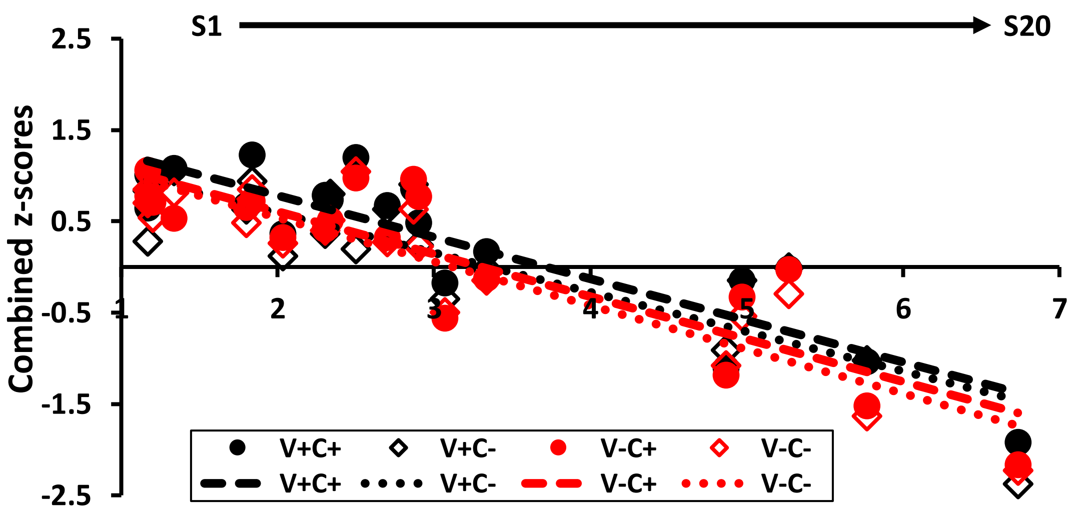


Figure 5.7.9: Mean combined z-scores (averaged across head pitch angle, gait speed and walking smoothness) for V+C+ (black, filled circles), V+C- (black, outlined diamonds), V-C+ (red, filled circles) and V-C- (red, outlined diamonds) conditions. Surfaces were rated from the easiest and simplest to traverse (S1) to the hardest and most complex (S20) using a surface perception scale from 1 (smooth / stable) to 10 (rough / unstable).

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Chapter Six: Surface complexity perception: does age or first-hand experience matter?

From our previous chapters, I have shown that perceptual measures of surface complexity offer an easy and simple proxy for behavioural changes. Perceptual measures are highly correlated to physical measures of the surface (see Chapter 3) and have consistently predicted gaze and gait behavioural changes (Chapters 3, 4 and 5). However, thus far, I have only assessed the perception of surface complexity from young people, whilst older people are more at risk of an injurious fall. In this chapter, the aim was to determine whether surface complexity was perceived similarly in young people to older people. I also wanted to determine whether first-hand experience of the surface was important for perception ratings given. As public walkway surfaces are typically repaired and replaced by the perception of the surface from a single individual, infrequently and first-hand, could a photo of the surface produce comparable perception results? I also, therefore, aimed to compare the perception ratings of surfaces given from first-hand experience to the same surfaces viewed from a single image.

6.1 Abstract

Background: In an attempt to reduce fall risk and ensure gait stability, we typically adopt a more cautious gait as we age, especially over more complex, outdoor surfaces. However, it is not known whether these age-related behavioural changes influence how walking surfaces are perceived. Surface perception is particularly important given that decisions regarding complex surface repairs are typically determined by a single individual who assesses surfaces, first-hand. Inevitably this is done infrequently. We may therefore ask, does the age of the person making the assessment affect any such decision? Similarly, is first-hand experience necessary for such decisions, or would a less costly and time saving approach, namely determining surfaces complexity from a single image of the same surface produce comparable results? Therefore, to determine potential confounding factors affecting surface perception, this study considered both age (young vs older participants) and experience (first-hand vs viewing images) of individuals assessing surfaces of different complexities.

Research Question: How does perceived surface complexity, assessed from surface roughness and stability, change as we age, and secondly, do images of surfaces produce similar responses to first-hand experience?

Methods: We compared the perception ratings of surface roughness and stability across 17 surfaces for different groups of participants. We compared how young participants (aged 18 – 40) who rated online images of surfaces first-hand compared to, firstly, older (aged 65 - 93) participants who also rated online images of surfaces and secondly, to young participants (aged 18 – 38) who rated surfaces first-hand. Additionally, all participants were asked to describe surfaces in a maximum of three words.

Results: Neither the age of participants (young vs older) nor experience of surfaces (first-hand vs images) had a large effect on perceived ratings. Only a small number of surfaces showed significant differences between the three groups, and ratings were significantly correlated between different participant groups. Likewise, overall surface descriptions were similar between groups and different surfaces were described in similar descriptions.

Significance: Our study showed that neither age nor experience significantly changed the perception of surface complexity. This suggests that, with age, surfaces are perceived similarly despite the increased risk of an injurious fall. Separately, our finding suggests surface complexity assessment may be completed as effectively when done remotely, using a single image. Together these findings increase the potential for walking surfaces to be assessed more easily and frequently to help prevent incidences of injury from falls when walking outdoors.

6.2 Introduction

Falls are one of the leading causes for injury with age, over 7 million injuries from falls being reported each year for those over 65 in the USA alone (Bergen, Stevens, & Burns, 2016). Increased injury risk from falls with age is likely caused as a result of increased prevalence of a fall, due to age-related comorbidities (including vision and cognitive decline), as well as increased injury rate due to loss of musculoskeletal strength. In a supposed response to reduce fall risk, researchers have identified certain behavioural changes, found when walking with age, collectively termed "cautious gait" (Herman, Giladi, Gurevich, & Hausdorff, 2005; Nutt, 2001). These responses suggest that, even with age-related deteriorations, older individuals can perceive when conditions are more challenging with respects to their abilities and change behaviour accordingly. Despite this finding, falls are still commonplace for this population group. For both older and young individuals, falls are common when outdoors and when surfaces are non-level. Uneven surfaces and steps are regularly reported as the most common environmental factor for a fall (Gazibara, et al., 2017; Nyman, Ballinger, Phillips, & Newton, 2013; Talbot, Musiol, Witham, & Metter, 2005) with both older and young individuals having to adapt their behaviour under these more challenging conditions ('t Hart & Einhauser, 2012; Marigold & Patla, 2008; Matthis, Yates, & Hayhoe, 2018; Voloshina, Kuo, Daley, & Ferris, 2013). However, given that older individuals already show a more cautious gait in general, do older individuals perceive these more complex surfaces differently to the young? Alternatively, does the adoption of an existing cautious gait help them feel more stable and thus perceive surfaces similarly to the young? Understanding the perception of surfaces, and potential differences between the young and the older individuals, may help us understand why there is a greater risk of a fall as we age. Furthermore, surface perception for either both, or one age group, may prove to be a useful metric in determining overall surface complexity.

Surface complexity is an important parameter to evaluate the risk of a fall in a given setting. However, there are few existing studies that have been conducted to assess the perceived measure of surface complexity and how this may relate to fall risk. In the UK, individual councils are responsible for pavement maintenance; decisions towards resurfacing or pavement repair made entirely by one individual's perception of conditions (for example see Surrey County Council, 2008). However, pavements do not represent all surfaces on which we may walk and, as mentioned above, perception of conditions may be affected by the individual's age. As such, using the existing approach, the decision to replace or resurface a pavement may be affected according to the individuals' age. A recently developed metric for pavement surface complexity, the Sidewalk Condition Index (Corazza, Di Mascio, & Moretti, 2016), assesses walking surfaces based on the presence of set features (e.g. roots, cracks and potholes). However, similarly this measurement relies, in part, on the individual's perception of surface conditions. We contend that a more formally validated approach is required. The approach taken by the current authors, presented here and in our previous research, assessed the perception of surface complexity from multiple individuals of a similarly aged population (Thomas, Gardiner, Crompton, & Lawson, 2020a, 2020b). As such, the current study procedure can identify surfaces that are consistently considered of greater fall risk for populations of similar age.

One research area where surface perception has been formally related to fall risk is the effect of floor slipperiness. For example, Cohen and Cohen (1994) assessed the perception of outdoor surfaces under dry and wet conditions, both from observation and after having walked on the surface. Most surfaces tested were perceived as more slippery when they were wet, and observation ratings were highly correlated with experience of walking over the surface. This finding suggests that perceptions of surface slipperiness from observation are as accurate as those resulting from having walked over it. Other studies have determined differences in perceived slipperiness for surfaces of different complexities. For example, although assessments of floor tiles of different roughness showed no differences in perceived slipperiness (Li, Chang, Leamon, & Chen, 2004), longer stretches of walkways showed smooth surfaces to be perceived as more slippery than rough surfaces (Yu & Li, 2015). However, these studies tested healthy younger individuals. One large-cohort study has suggested that the perception of older individuals is as good as that of the young; the perception of balance in older individuals being highly associated with levels of walking activity, unlike actual balance performance (Talkowski, Brach, Studenski, & Newman, 2008). Similarly, both older and young adults were able to identify stairs that were too high to safely traverse (Konczak, Meeuwsen, & Cress, 1992). However, in contrast, a study from Lockhart, Woldstad, Smith, and Ramsey (2002) showed a greater discrepancy between the perceptual ratings of surface slipperiness between observation and experience in older participants compared to the young. Therefore, further research is required for elucidation of the relationship between age and surface perception.

Another factor that may affect how complex a surface is perceived comes from how the surface is viewed. In the present study, we compared perceived surface complexity under real life ("first-hand") conditions to a single image of the same surfaces. To the authors' knowledge, no study has contrasted subjects' assessments of walking surface complexity between first-hand experience and images. However, previous research has shown no differences between the perceived steepness of stairs for first-hand experience compared to images of the same surfaces (Taylor-Covill & Eves, 2013). Furthermore, we might expect that differences between surface complexity can be shown from images given that previous research was able to demonstrate differences for assessment of floor slipperiness using surface images alone (Zamora, Alcántara, Artacho, & Cloquell, 2008). In the present study we tested whether surface perception differed when assessed from surface images compared with first-hand experience. This might be expected, given that, in viewing the surface first-hand, the individual can use stereoscopic information and use a larger field of view to assess the complexity of the surface. This information, not available from images, may change the perspective of the surface. On the other hand, if images (taken under settings to that of first-hand conditions) show comparable results to direct observation, this may allow for an easier and more automated method to determine surface complexity perception. This would be of particular interest for council-made decisions for pavement maintenance, the public being potentially able to submit images of surfaces that are deemed to be of increased fall risk, or records being made at intervals via automated camera systems.

To determine the importance of experience and age for surface perception, we investigated surface perception for two age groups (young and older individuals) and, for young individuals, for two experiences (first-hand and online images). Older individual perception first-hand was not assessed due to the increased risk of a fall and injury to these participants when walking. For all conditions, we assessed surface complexity using Likert scales (Likert, 1932) of perceived surface roughness and perceived stability. By assessing both measures, we can interpret and compare how different participants perceived surface roughness (e.g. “completely smooth”, “extremely rough”) and how different participants perceive their likely locomotion if they were to walk over the surface (e.g. “no problem with stability”, “I think I might fall over”). In addressing the above questions, we can better understand how to assess surface complexity in relation to fall risk. This is particularly meaningful given our previous findings that showed that perception of surfaces was strongly correlated with both physical and behavioural changes in the young (Thomas, et al., 2020b).

6.3 Methodology

We assessed the perceived surface complexity from three groups of participants based on age (young vs older individuals) and experience (first-hand vs online image).

6.3.1 Participants

Participants were grouped as: young online image (YOI), older online-image (OOI) and young first-hand participants (YFH). The YOI group consisted of 41 participants, aged 18 – 40, (4 male, mean ± SD; age = 23.3 ± 5.7; height = 166.0 ± 7.8; weight = 68.1 ± 24.3). Participants were predominately undergraduate university students recruited from a psychology experimental participation group. The OOI group consisted of 37 participants, aged 65 – 93, (14 male, mean ± SD; age = 74.6 ± 7.1; height = 169.0 ± 8.7; weight = 67.2 ± 12.0). Participants were recruited from local U3A (University of the Third Age) groups. The YFH group consisted of 32 participants, aged 18 – 38 (14 male, mean ± SD; age = 22.2 ± 5.0; height = 172.6 ± 8.5). Participants were predominately University students. The perception data for these participants has been previously reported (Thomas, et al., 2020b), and is presented here again in order to compare this group to the other two groups. We tried to ensure that participants completed the study under similar conditions both to each other and to the images used for online image participants. Specifically, all participants were tested on dry and overcast days either mid-morning or mid-afternoon.

6.3.2 Data collection & Protocol

The data collection procedure was similar for all participants. Participants from all three groups rated 17 surfaces (**Figure 1**) on Likert scales (Likert, 1932) for perceived surface complexity. Surfaces were chosen to cover a wide range of those encountered in daily-life, all surfaces being located within The University of Liverpool campus. In selecting 17 surfaces, this study assessed a larger number of surfaces than that had been previously assessed using perceptual ratings (Cohen & Cohen, 1994; Li, et al., 2004; Yu & Li, 2015). Surface complexity was determined from two separate measures, participants rating the perceived surface roughness (1 = "Completely smooth" to 10 = "Extremely rough") and perceived stability (1 = "No problem with stability" to 10 = "I would probably fall over") if they were to walk on the surface. Participants were also asked to describe each surface in a maximum of three words. Similar descriptions were pooled together (e.g. paved and paving), for details see supplementary material **Table 6.7.1**. For both YOI and OOI participants, the study was completed using Qualtrics software (Qualtrics, Provo, UT). Participants were shown a single image and written description for each surface. Descriptions of the surfaces (see supplementary material **6.7.2**) and a dashed red arrow on the image denoted the start- and end for each surface (see **Figure 1**). Any features that were of note, but that could not be easily seen due to the angle of the image (e.g. steps), were highlighted in the description and in the picture using a red star. Ratings were recorded using Likert scales provided and descriptions could be typed into a text box. For the YFH participants, the research investigator informed the participant of the start- and end-point for each surface, pointing out any notable features or requirements (e.g.

“walk down the steps” etc.). Participants would then give ratings and descriptions for each surface vocally, recorded by the research investigator. All participants rated surfaces in order from S1 to S17.

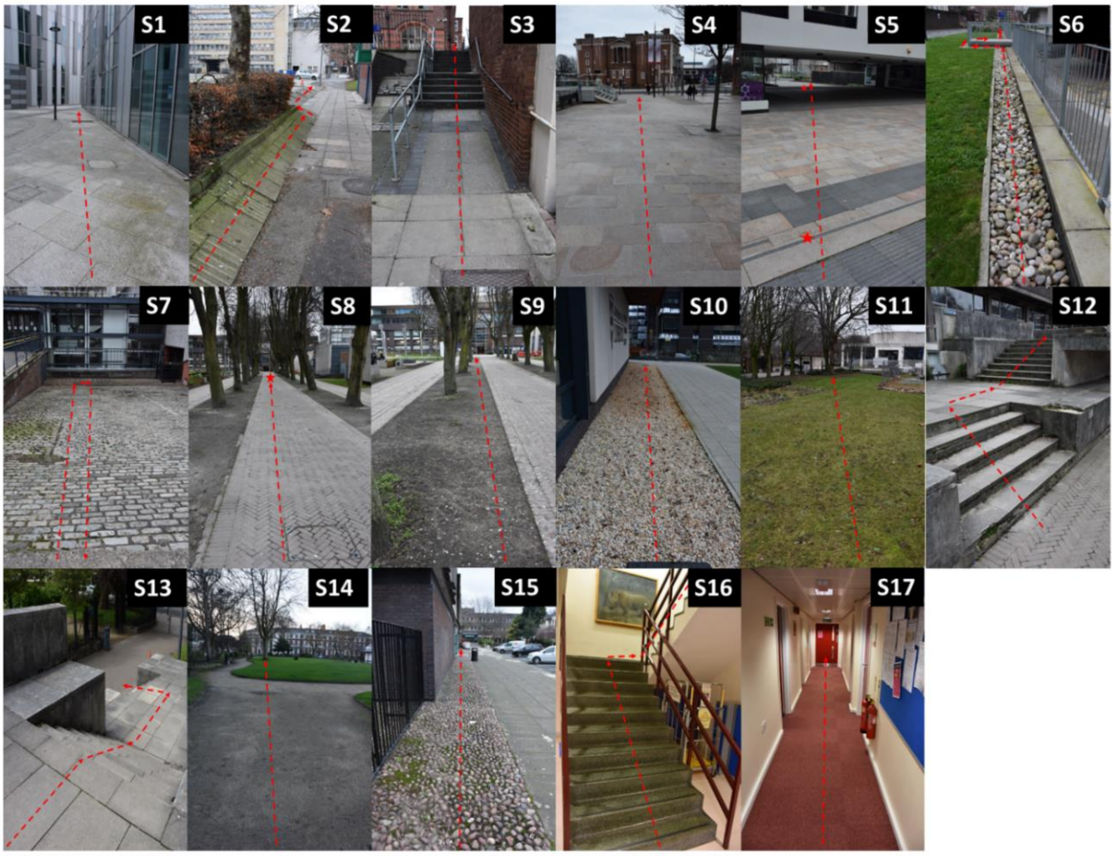


Figure 1: Images showing the 17 surfaces, shown in the order presented to all participants (S1 – S17). YOI and OOI participants were shown the above pictures, accompanied by a description which denoted the start and end for each surface. For surfaces that included features not easily shown on the image, additional information was given in the description, highlighted in the image using red stars.

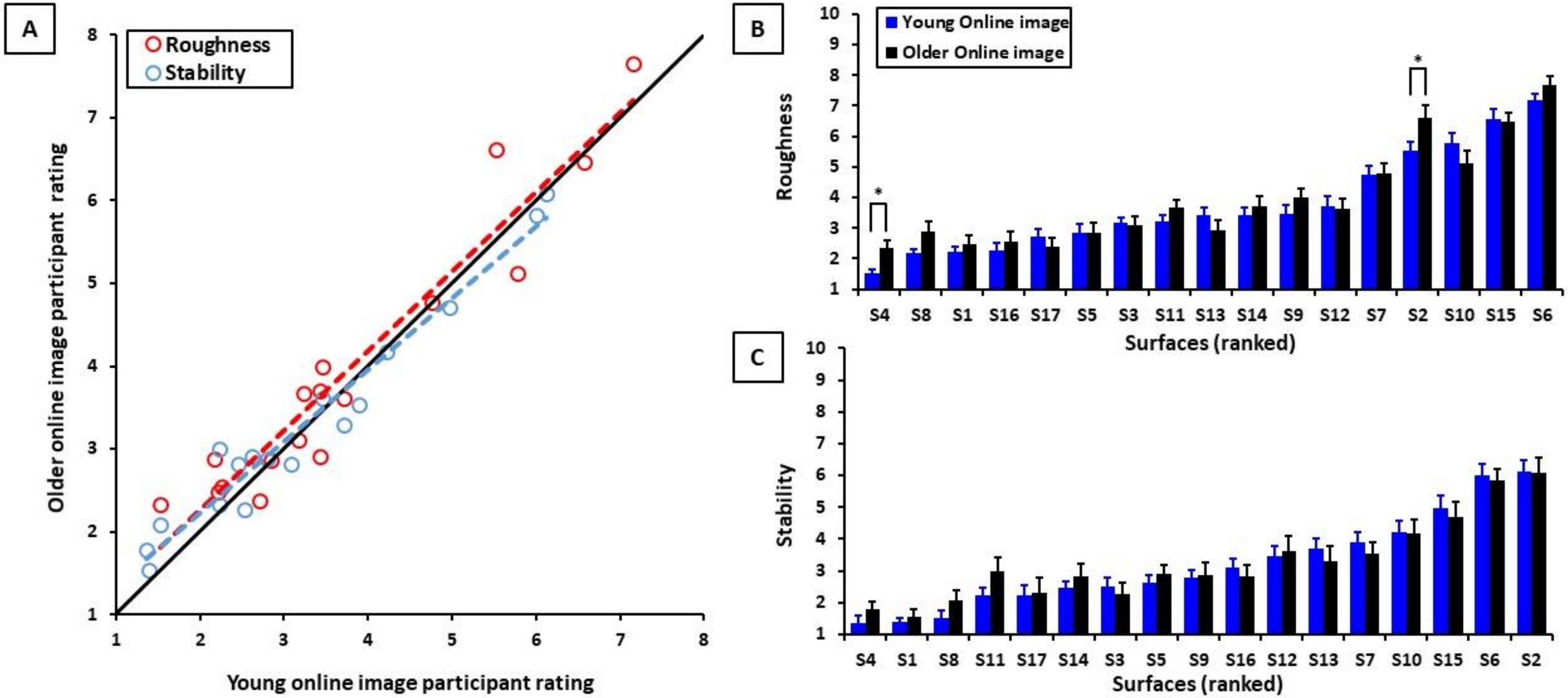
6.3.3 Analysis

We conducted linear regression for both roughness and stability mean ratings, comparing YOI participants to OOI and then YFH participants. To compare differences in ratings between participant groups, we conducted t-tests between the regression line intercepts and slopes. We also conducted a one-way ANOVA for ratings given at the surface level. Finally, we pooled common descriptions for surfaces and compared the frequency of these words for different surfaces. Significant differences were determined as those with a p value of less than 0.05 and effect sizes were categorised as small ($d > 0.2$) , medium ($d > 0.5$) or large ($d > 0.8$) following Cohen (2013).

6.4 Results

Mean roughness and stability ratings for YOI and OOI participants are shown in **Figure 2A**. A linear regression showed a significant relation between young online image participants and older online image participants for both roughness and stability ratings, ($R^2 = 0.91$; $F,(1,16) = 169.81$, $p < 0.001$ and $R^2 = 0.95$; $F,(1,16) = 316.86$, $p < 0.001$ respectively). However, there were no significant differences between the roughness and stability regression intercepts ($t(33) = 0.46$, $p = 0.01$) or between regression slopes ($t(33) = 1.05$, $p = 0.003$). Thus, surfaces perceived as rougher and less stable for YOI participants, were similarly rated by OOI participants. Comparison between groups at the surface level showed significant differences in perceived roughness (**Figure 2B**) for two surfaces (S2 and S4), ($t(75) = -2.66$, $d = 0.63$, $p = 0.01$; $t(72) = -2.70$, $d = 0.07$, $p = 0.009$ respectively). For both surfaces, the OOI participants perceived surfaces to be significantly rougher than YOI participants. However, there were no other significant differences for surface roughness and no significant for perceived stability (**Figure 2C**), see supplementary material (**Table 6.7.3**) for details.

Mean roughness and stability ratings for YOI and YFH participants are shown in **Figures 2D**. A linear regression showed a significant relation between YOI participants and YFH participants for both roughness and stability ratings, ($R^2 = 0.96$; $F_{,(1,16)} = 378.06$, $p < 0.001$ and $R^2 = 0.91$; $F_{,(1,16)} = 167.00$, $p < 0.001$ respectively). However, there were no significant differences between the roughness and stability regression intercepts *($t(33) = -0.74$, $p = 0.465$)* or between regression slopes *($t(33) = 0.80$, $p = 0.431$*. Thus, surfaces perceived as rougher and less stable for YOI participants, were similarly rated by YFH participants. Comparison between groups at the surface level showed significant differences in perceived stability (**Figure 2F**) for surfaces S2, ($t(67) = -2.63$, $d = 0.70$, $p = 0.011$. The YFH participants perceived this surface to be significantly more unstable. However, there were no other significant differences for stability and no significant differences for perceived roughness (**Figure 2E**), see supplementary material (**Table 6.7.3**) for details.



A
Roughness
Stability
Older online image participant rating
Young online image participant rating
B
Young Online image
Older Online image
Roughness
S4 S8 S1 S16 S17 S5 S3 S11 S13 S14 S9 S12 S7 S2 S10 S15 S6
Surfaces (ranked)
C
Stability
S4 S1 S8 S11 S17 S14 S3 S5 S9 S16 S12 S13 S7 S10 S15 S6 S2
Surfaces (ranked)

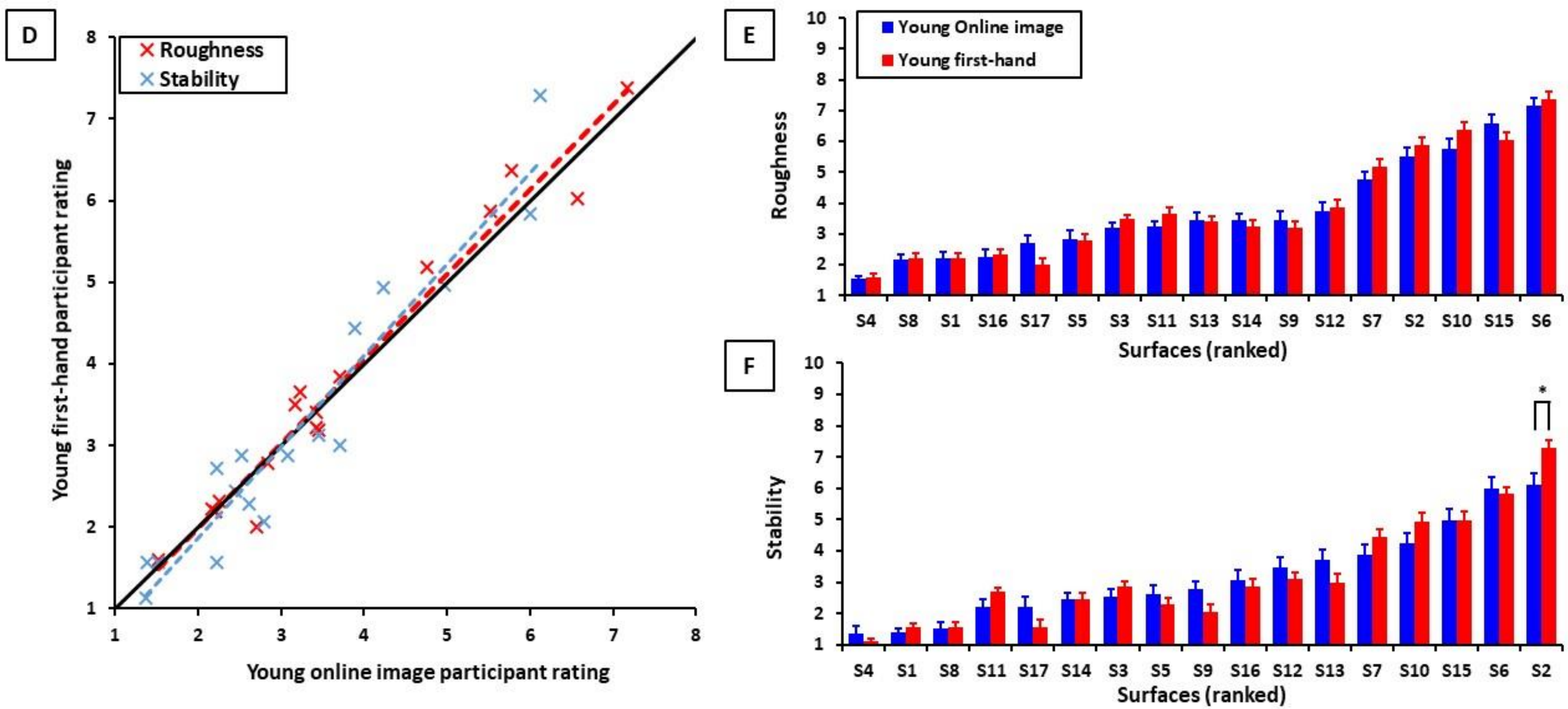


Figure 2: Mean roughness and stability ratings between YOI participants and (**A**) OOI participants and (**D**) YFH participants. The black lines represents a correlation of R = 1 and dotted lines represent the regression lines for roughness (red) and stability (blue). The linear regression equations are as follows: (**A**) roughness = $R^2 = 0.91$ ($y = 0.96x + 0.34$) and stability = $R^2 = 0.95$ ($y = 0.86x + 0.50$), (**D**) roughness = $R^2 = 0.96$ (y

= 1.04x – 0.11) and stability = $R^2 = 0.92$ (y = 1.12x - 0.39). Surface mean (± SE) roughness ratings and stability ratings for YOI participants are shown when compared to (**B, C**) OOI image participants and (**E, F**) YFH participants. Surfaces are ranked from least rough/most stable to most rough/least stable according to ratings from YOI participants. Significant differences (*) between YOI participants and each other respective participant group are shown for each surface and are considered significant at $p < 0.05$.

Participants for each group were also asked to give a maximum of three descriptions for each surface. The five most common descriptions for each group, and shared amongst all groups, are shown in **Table 1**. Descriptions were generally similar between groups, however the older online image group commonly referred to a "handrail" (either present or lacking, n = 45), which was not commonly reported by either the young first-hand (n = 0) or young online image group (n = 6). The most common descriptions that were shared amongst groups were "smooth", "steps", "stairs", "uneven" and "paved." The frequency for these descriptions used at each surface for each group is shown in **Figure 3**. Descriptions at each surface were generally similar between groups. "Smooth" was more frequently used for surfaces that had lower surface complexity ratings, whilst the description "uneven" was more frequently used for surfaces will higher surface complexity ratings. Notably, some of the older online image participants described S1 and S4 as "uneven", despite a low roughness and unstable rating. Furthermore, this description was not used by other participant groups. Across all participants, the descriptions "steps" and "stairs" were used similarly between surfaces and "paved" was used more frequently for surfaces that had lower surface complexity ratings.

Table 1: The frequency of the five most common verbal descriptions provided by participants in each of the three groups. Descriptions are listed in order, shown as percentages (actual number) of the total number of words given.

Young first-hand		Young online image		Older online image		All participants	
stairs	8.8% (97)	smooth	15.2% (178)	smooth	11.4% (131)	smooth	11.6% (396)
smooth	7.6% (84)	uneven	6.7% (78)	steps	7.4% (85)	steps	6.0% (206)

paved	6.1% (67)	stairs	6.5% (76)	uneven	6.3% 73	stairs	5.7% (194)
steps	5.9% (65)	old	6.0% (70)	paved	4.2% (48)	uneven	5.6% (192)
grassy	4.7% (52)	steps	4.6% (54)	handrai l	3.9% (45)	paved	4.9% (167)
	100% (1107)		**100% (1168)**		**100% (1151)**		**100% (3426)**

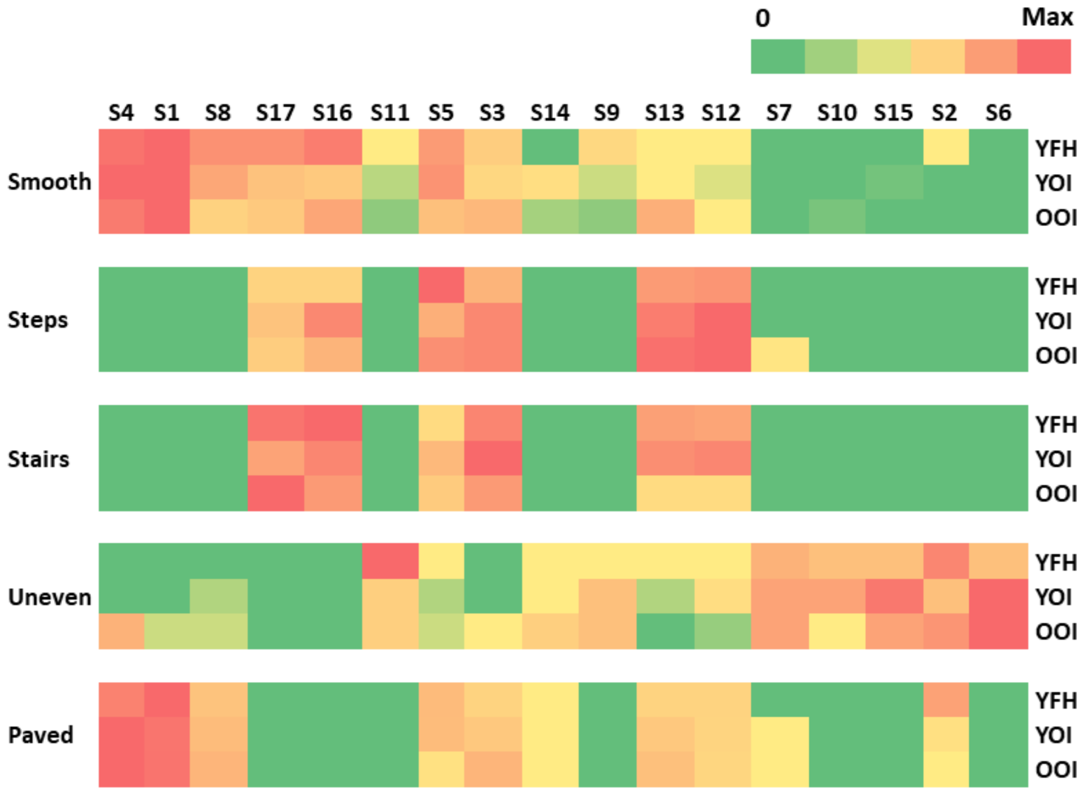


Figure 3: A heat map showing the frequency of each of the five most common descriptions given for each participant group; young first-hand participants (YFH), young online image participants (YOI) and older online image participants (OOI). Surfaces are ordered from the least (S4) to most (S6) complex, as calculated from the average rating between the roughness and stability ratings for YOI participants. Heat maps were calculated based on the frequency of the description being used across

surfaces for each participant group, from no incidence (darkest green) to the highest frequency of the word-use (darkest red).

6.5 Discussion

The aim of this study was to determine whether perceptual measures of surface complexity, measured from perceived surface roughness and stability, differed depending on the age of the participant and how the surfaces were viewed. The results showed that neither age nor experience had a large effect on perception ratings. Compared to young participants viewing surfaces from online images, there were only three incidences of significant differences at the surface level between ratings, two for older participant's roughness ratings (S4 and S2) and one for young first-hand participant's stability ratings (S2). Moreover, for both groups, roughness and stability ratings were closely correlated with young online image participants, correlations over R = 0.9. Thus, surface complexity perception does not seem to change dependent on age nor experience.

The perception of surface conditions is one of the factors that dictates whether improvements to pavements and public walkways are required. Currently, in the UK, only one or a small number of individuals are included in this decision, made first-hand at the location. This procedure may be problematic given the changeable nature of walking surfaces from different environmental factors, such as slipperiness, known to impact perceived fall risk (Cohen & Cohen, 1994; Yu & Li, 2015). Furthermore, there are currently inconsistent findings regarding the perception of fall risk associated with walking surfaces as we age (Lockhart, et al., 2002; Talkowski, et al., 2008). The results of the present study suggest that neither age nor experience significantly changes the perception of surfaces. This finding suggests that the age of the individual or researcher assessing fall risk from a surface should not influence their assessment. This is particularly of note given that this finding was consistent across the clear majority of surfaces in the present study, including surfaces described as smooth, uneven, paved and grassy as well as for stairs. Furthermore, the study showed no differences from the perceived complexity from first-hand experience to that when looking at an online image. This supports previous research that showed images of stairs to exhibit a similar perceived steepness to the same stairs in situ (Taylor-Covill & Eves, 2013). The results presented here may have implications towards the future assessment for surface replacement or repairs, individuals potentially able to view surfaces from online images only. This procedure could be beneficial toward reducing the time taken to replace potentially dangerous surfaces, given that images could be taken more easily by pedestrians, rather than be ascertained by council workers in situ. Furthermore, this procedure could allow surfaces to be assessed more regularly, including across numerous weather conditions, and thus be implemented as a similar procedure to that used for UK road repair, assessed using the TRAffic-speed Condition Survey (TRACS), (see Scott, et al., 2008). The use of online images to assess surface complexity would also allow surface assessment to be done more quickly, meaning the potential for multiple individuals to assess the same surfaces at the same time to prevent anomalies, as performed here. In doing so, surfaces that are of higher risk of a fall, including uneven surfaces and steps, could be assessed more frequently in the hope to prevent the number of falls.

Across all participant groups, surfaces were largely described similarly in relation to perceived complexity ratings. For example, surfaces S6 and S2 were perceived as the most rough, and the least stable respectively and were both commonly referred to as “uneven”. Individually the surfaces consisted of a stony surface and a sloped surface respectively, as shown in **Figure 1**. Notably, similar surface types have been used in previous research when wanting to assess behaviour over complex and uneven conditions (Marigold & Patla, 2007; Merryweather, Yoo, & Bloswick, 2011). Equally, surface S4 was rated as the least rough and most stable and commonly described as “smooth” by all groups. This surface consisted of paving slabs, previous research using paving slabs to represent smooth surfaces (Thies, et al., 2011). As participants from all groups commonly described these two types of surfaces as “smooth” and “uneven”, this suggests that previous researchers were correct in defining those surfaces as such and using them as representations for more simple and more complex surfaces respectively. Our other research has supported these findings; the surfaces perceived as more rough and described commonly as “uneven” here shown to exhibit behaviour indicative of a more cautious gait, as expected under more challenging conditions (Thomas, et al., 2020b).

In this study we pooled participants into one of two age categories (young or older). However, increasing age is known to be associated with an increased number of comorbidities, which in turn increase the risk of falls (Barnett, et al., 2012). To determine whether the age of participants within age groups affected ratings, we calculated overall roughness and stability ratings (averaged across all surface) for each individual (see supplementary material **6.7.4**) and regressed these against their age. Age within each of our three group was not shown to be a significant predictor of roughness or stability ratings. However, for OOI participants, a slight trend does appear to exist such that increased age led to higher (more unstable) stability scores. Thus, future research could evaluate this further, testing a greater balance of participants at each age compared to that found here, to see whether age or other confounding factors (e.g. activity levels or number of existing health conditions) may more accurately predict perceived surface complexity.

6.6 Conclusion

In summary we found that perception was not affected by participant age or whether participants only saw surface images. Perceptual ratings of surface roughness and stability were highly correlated between different conditions and descriptions were largely similar. The study did not include first-hand assessment for older participants, and thus we do not know whether surfaces are perceived differently for this population group. Although there were few differences between surface ratings for the older and young group when viewing surface from a single image, the older individuals did describe less complex surfaces (S4 and S1) as uneven and did often describe surfaces in relation to handrails. Future research should test a range of surfaces of different complexities under additional conditions, indicative of those likely to impact outdoor surface perception, including other environmental factors including presence of others, slipperiness and under different lighting conditions. In combination with the results of the current study, this would aid in the assessment of potentially high-risk surfaces and thus help to prevent and reduce injurious falls.

6.7 Supplementary Material

Table 6.7.1: Words entered into the analysis when similar, alternative descriptions were given. This was determined by one of the research investigators and was only used to collate words with the same or similar roots but different suffixes. All words belonging to the same root counted toward the same description count.

Word used in analysis	Alternative descriptions given
bricked	brick, bricks
bumpy	bumps
carpeted	carpet
cobbled	cobble, cobbles
downward	down, downhill
flagged	flag, flags
handrail	hand-railing, rail, rails
no handrail	(handrail) missing, no (handrail)
paved	pavement, paving
pebbled	pebble, pebbles
rough	roughened
slabbed	slab, slabs
slanted	slant, slants, slanting,
slippery	slippy
squishy	squidgy
stony	stoned, stone, stones
tiled	tile, tiling

trip-hazard	hazard, trip
upward	up, uphill
varied	variable, variation

6.7.2 Descriptions for each surface

Below are descriptions that accompanied each image of the 17 different surfaces shown to young and older online image participants. Description of surfaces were shown below the image of the same surface. Note that, for surfaces S16 and S17, an additional description was given above the picture that read, "***Note!*** *This surface includes some areas* ***not*** *shown in the picture. Please ensure to read the description before answering the questions!*"

- *S1. "Imagine walking in a straight line from where the photograph was taken to the end of the red arrow."*
- *S2. "Imagine walking from start of the red arrows (at the lower left corner of the photograph), then following the red arrows ending at the lamppost."*
- *S3. "Imagine walking from where the photograph was taken, and following the red arrow, ending at the top of the stairs."*
- *S4. "Imagine walking from where the photograph was taken, and following the red arrow, ending at the start of the crossing area."*
- *S5. "Imagine walking from where the photograph was taken, then going down one step (located at the lower star) and then following the red arrow, down three stairs (located at the upper star), ending at the corner of the dark bricked wall."*

- *S6. "Imagine walking from where the photograph was taken, then following the red arrows, ending at the bush at the far side."*
- *S7. "Imagine walking from where the photograph was taken, then following the red arrows down the ramp, before turning around and ending at the start location."*
- *S8. "Imagine walking from where the photograph was taken, then following the red arrow and ending where the star is located."*
- *S9. "Imagine walking from where the photograph was taken, then following the red arrow, ending at the end of the arrow."*
- *S10. "Imagine walking from where the photograph was taken, then following the red arrow, ending at the end of the arrow."*
- *S11. "Imagine walking from where the photograph was taken, then following the red arrow, ending in front of the tree."*
- *S12. "Imagine walking from the start of the red arrows (on the ground level), then following the red arrows up, ending at the end of arrows."*
- *S13. "Imagine walking from the start of the arrows (on the lower left side of the photograph), then following the red arrows, ending at the end of the arrows."*
- *S14. "Imagine walking from where the photograph was taken, then following the red arrow, ending in front of the tree."*
- *S15. "Imagine walking from where the photograph was taken, then following the red arrow, ending at the end of the arrow next to the white bins."*
- *S16. "You are now inside a building that has 3 floors (ground, first and second). Imagine walking from the ground floor (start of the red arrows) and then following the red arrows to the first floor (the top of the picture). You then*

need to keep walking to the top of the stairs on the second floor (not shown in the picture). The steps are the same size all the way up."

- *S17. "You are now inside a building that has 3 floors (ground, first and second). You are currently on the second floor. Imagine walking from where the picture was taken (the start of the red arrow) and then following the red arrow along the corridor and through the door. You then need to turn through another door on your right (not shown in the picture), and down the stairs to the first floor. We are in the same building as the previous surface (surface 16), so the stairs are similar in size and number. Please include both parts of the surface described when giving your ratings."*

Table 6.7.3: Mean perceived roughness and stability ratings for each surface for young online image, young first-hand and older online image participants. A one-way ANOVA was conducted between the three groups. Significant difference between young online image participants (in bold) and either older online image participants or young first-hand participants are considered as $p < 0.05$ (denoted in red).

		Roughness rating			Perceived stability rating		
		Young first-hand	**Young online image**	**Older online image**	**Young first-hand**	**Young online image**	**Older online image**
Surface 1	Mean (± SD)	2.2 (± 0.9)	**2.2 (± 0.9)**	2.5 (± 1.9)	1.6 (± 0.7)	**1.4 (± 0.8)**	1.5 (± 1.6)
Surface 2	Mean (± SD)	5.9 (± 1.6)	**5.5 (± 1.8)**	6.6 (± 1.7)	7.3 (± 1.2)	**6.1 (± 2.1)**	6.1 (± 2.3)
	p value			*0.010**	*0.011**		
	Cohen's d			*0.63*	*0.70*		
Surface 3	Mean (± SD)	3.5 (± 1.2)	**3.2 (± 1.1)**	3.1 (± 1.6)	2.8 (± 1.3)	**2.5 (± 1.6)**	2.3 (± 1.6)
Surface 4	Mean (± SD)	1.6 (± 0.7)	**1.5 (± 0.7)**	2.3 (± 1.7)	1.1 (± 0.3)	**1.4 (± 1.3)**	1.8 (± 1.6)
	p value			*0.009**			

	Cohen's d			*0.62*			
Surface 5	Mean (± SD)	2.8 (± 0.8)	**2.8 (± 1.0)**	2.9 (± 1.6)	2.3 (± 0.9)	**2.6 (± 1.7)**	2.9 (± 2.1)
Surface 6	Mean (± SD)	7.4 (± 1.4)	**7.2 (± 1.5)**	7.7 (± 1.9)	5.9 (± 1.6)	**6.0 (± 2.1)**	5.8 (± 2.8)
Surface 7	Mean (± SD)	5.2 (± 1.5)	**4.8 (± 1.6)**	4.8 (± 2.1)	4.4 (± 1.5)	**3.9 (± 1.9)**	3.5 (± 2.3)
Surface 8	Mean (± SD)	2.2 (± 1.1)	**2.2 (± 1.1)**	2.8 (± 1.7)	1.6 (± 1.0)	**1.5 (± 1.2)**	2.1 (± 1.8)
Surface 9	Mean (± SD)	3.2 (± 1.3)	**3.5 (± 1.4)**	4.0 (± 2.0)	2.1 (± 1.4)	**2.8 (± 1.8)**	2.9 (± 2.1)
Surface 10	Mean (± SD)	6.3 (± 1.4)	**5.8 (± 1.7)**	5.1 (± 2.3)	4.9 (± 1.6)	**4.2 (± 2.2)**	4.2 (± 2.8)
Surface 11	Mean (± SD)	3.7 (± 1.2)	**3.2 (± 1.7)**	3.7 (± 1.9)	2.7 (± 1.2)	**2.2 (± 1.4)**	3.0 (± 2.4)
Surface 12	Mean (± SD)	3.8 (± 1.5)	**3.7 (± 1.9)**	3.6 (± 2.1)	3.1 (± 1.5)	**3.4 (± 1.9)**	3.6 (± 3.0)
Surface 13	Mean (± SD)	3.4 (± 1.4)	**3.4 (± 1.7)**	2.9 (± 1.9)	3.0 (± 1.2)	**3.7 (± 2.1)**	3.3 (± 2.9)
Surface 14	Mean (± SD)	3.2 (± 1.1)	**3.4 (± 1.5)**	3.7 (± 2.1)	2.4 (± 1.5)	**2.5 (± 1.4)**	2.8 (± 2.4)
Surface 15	Mean (± SD)	6.0 (± 1.5)	**6.6 (± 2.0)**	6.5 (± 2.4)	5.0 (± 1.7)	**5.0 (± 2.3)**	4.7 (± 2.8)
Surface 16	Mean (± SD)	2.3 (± 1.2)	**2.3 (± 1.4)**	2.5 (± 1.8)	2.9 (± 1.4)	**3.1 (± 2.0)**	2.8 (± 2.7)
Surface 17	Mean (± SD)	2.0 (± 1.1)	**2.7 (± 1.5)**	2.4 (± 2.0)	1.6 (± 0.7)	**2.2 (± 1.4)**	2.3 (± 2.5)

6.7.4 Individual's age effect on ratings

The overall surface ratings (average rating regardless of surface type) were calculated for roughness and stability ratings for each individual. The overall surface ratings within each age group (YFH, YOI, OOI) are shown in Figures 6.7.4.1, 6.7.4.2 and 6.7.4.3 respectively. A linear regression showed no significant relation between YFH age and roughness or between age and stability (R^2 = 0.001; F,(1,31) = 0.02, $p = 0.897$ and R^2 = 0.01; F,(1,31) = 0.29, $p = 0.597$ respectively). This was similarly the case for YOI (R^2 = 0.04; F,(1,40) = 1.64, $p = 0.209$ and R^2 = 0.001; F,(1,41) = 0.03, $p = 0.868$) and OOI participants (R^2 = 0.03; F,(1,36) = 0.94, $p = 0.339$ and R^2 = 0.08; F,(1,36) = 3.13, $p = 0.086$). It should be noted that, although not significant, for

OOI participants, a slight trend exists such that increasing age did produce higher overall surface rating scores.

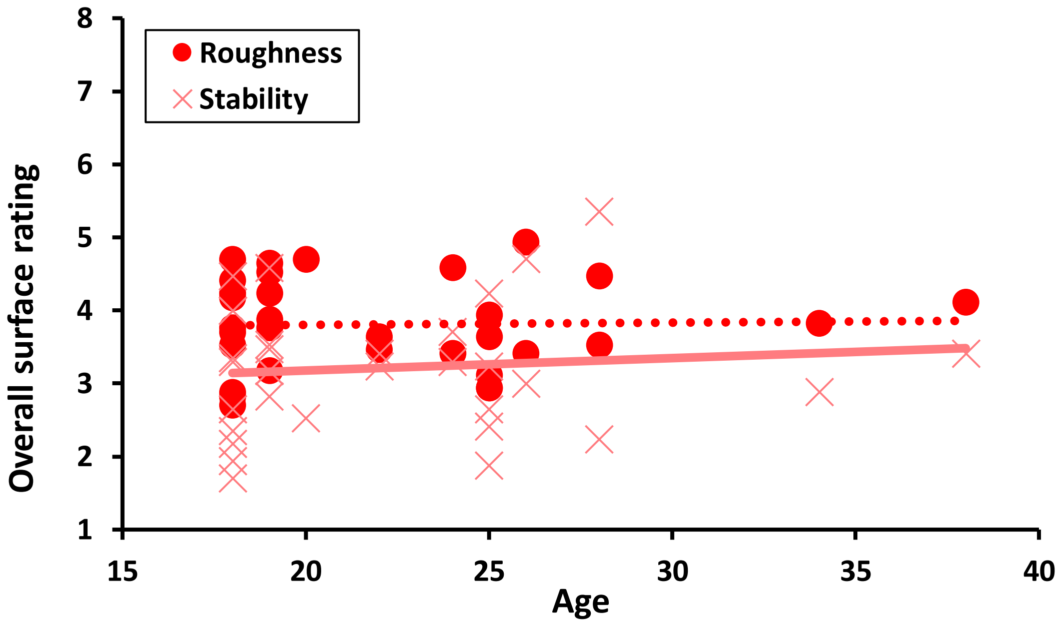


Figure 6.7.4.1: Overall surface ratings for roughness (red circles) and stability (pink crosses) for each YFH individual based on their age. The red dotted and pink solid lines represent the regression lines for roughness and stability respectively. The linear regression equations are: roughness = $R^2 = 0.001$ ($y = 0.003x + 3.74$) and stability = $R^2 = 0.01$ ($y = 0.002x + 2.84$).

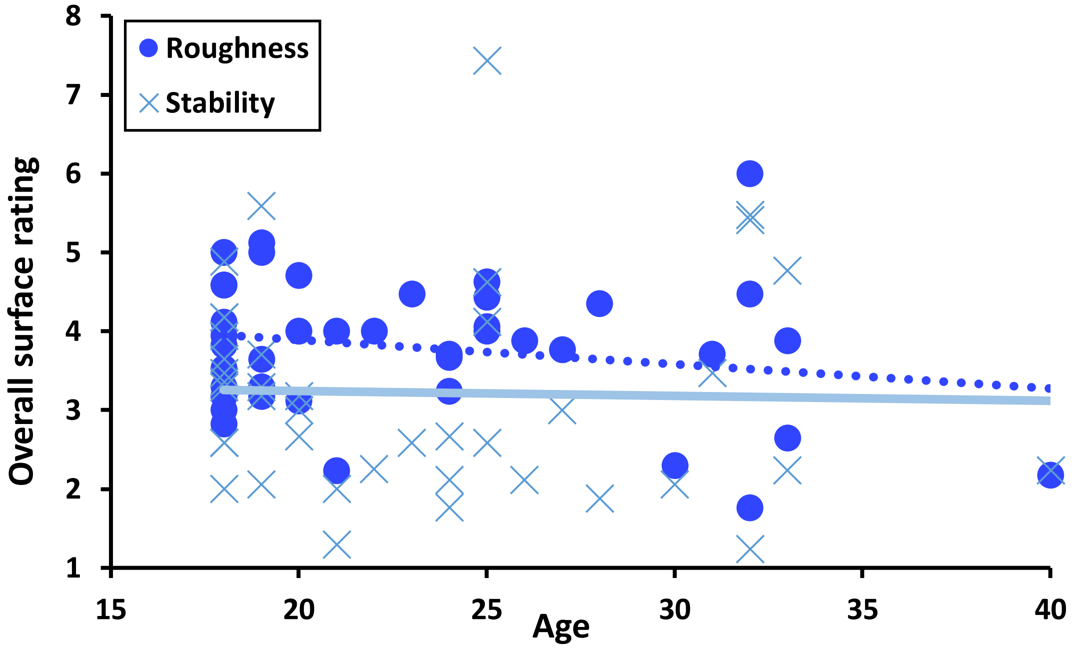


Figure 6.7.4.2: Overall surface ratings for roughness (blue circles) and stability (light blue crosses) for each YOI individual based on their age. The blue dotted and light blue solid lines represent the regression lines for roughness and stability respectively. The linear regression equations are: roughness = R^2 = 0.04 (y = 0.03x + 4.51) and stability = R^2 = 0.001 (y = 0.01x + 3.37).

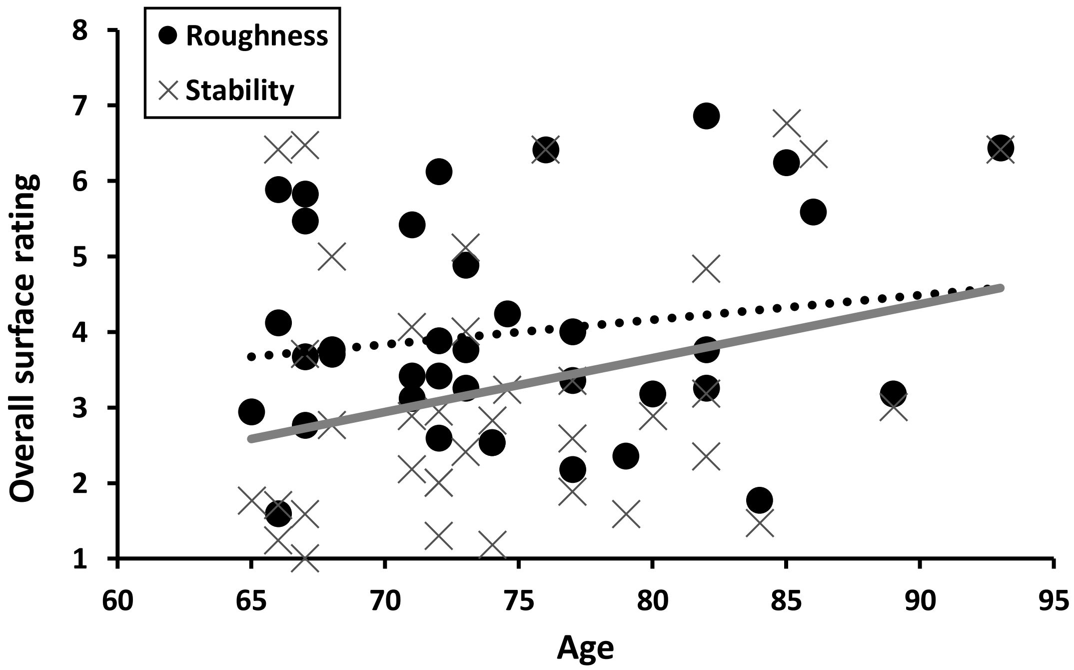


Figure 6.7.4.3: Overall surface ratings for roughness (black circles) and stability (grey crosses) for each OOI individual based on their age. The black dotted and grey solid lines represent the regression lines for roughness and stability respectively. The linear regression equations are: roughness = $R^2 = 0.03$ ($y = 0.03x + 1.55$) and stability = $R^2 = 0.08$ ($y = 0.07x - 2.06$).

6.8 References

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Chapter Seven: General Discussion

The final chapter of this thesis provides a general discussion of the findings presented herein and considers how they may be used to direct future research.

7.1 Thesis Summary

The goal of the research conducted for this thesis was to advance the understanding of natural human locomotion (i.e. outside laboratory conditions), and to explore further how locomotion may change under different conditions. I wished to determine how specific intrinsic and extrinsic factors affected gait stability in order to recognise why there is a heightened fall risk with both increasing age and in certain environmental settings.

I believe that the findings of this thesis can be separated into two main conclusions, which are listed as 7.1.1 and 7.1.2:

7.1.1 Extrinsic factors had a substantial effect on gaze and gait behaviour.

7.1.2 Perception measures of surface complexity may provide a simple measure indicative of instability.

7.1.1 Extrinsic factors effect gaze and gait behaviour

The first main conclusion from this thesis was that extrinsic factors had a substantial effect on behaviour. Increased surface complexity was associated with changes in gaze and gait behaviour, found consistently across individual experiments (see Chapters 2, 4 and 5).

Head pitch was a clear indicator of behavioural change in response to substrate complexity: a lowered head pitch directed closer to the person's feet consistently found when traversing more complex surfaces. Furthermore, more complex surfaces were associated with a reduced walking speed, reduced walking smoothness (as measured from harmonic ratios) and increased muscle coactivation (see Chapters 4 and 5). All these responses are indicative of either an increased perceived fall risk or of more hazardous behaviour associated with heightened fall risk (Doi, et al., 2013; Menz, Lord, & Fitzpatrick, 2003; Peterson & Martin, 2010; Voloshina, Kuo, Daley, & Ferris, 2013). Although not traditionally determined as a measure of perceived or actual fall risk, the measures assessed here may act as an alternative indicator of gait stability being compromised. This approach, namely determining instability from numerous sources of behavioural change, avoids any possible bias from assessing instability from single stability measures (reviewed in Bruijn, Meijer, Beek, & Van Dieën, 2013).

In our research, gaze behaviour was determined from both eye and head pitch angle. In doing so, we showed that head pitch made a significant contribution to overall gaze, particularly when walking over the most complex of surfaces (Chapter 2). Gaze has typically not been determined from both eye and head pitch movements, although our findings suggest there are only weak relationships between mean angles of the eyes and head. Moreover, our studies showed that eye angle, fixation duration and the number of fixations, all common variables used in studies of behavioural changes and fall risk when walking, did not reveal consistent patterns of behavioural change across studies (Chapters 4 and 5). We speculated that since eye movements are likely to be more variable than head movements, which is likely to change more based on environment-specific factors (particularly when walking outdoors), assessing eye movements alone may lead to misleading interpretation of results. Therefore, future research should consider *both* eye and head movements in order to more fully comprehend those factors associated with changes in gaze behaviour. Furthermore, of the two, head movements may be more informative, particularly when studying stability or if testing studies in more challenging conditions outside the laboratory.

Unlike surface complexity, intrinsic factors (simulated lower visual field loss and, to a greater extent, simulated reduced cognitive capacity) were not associated with substantial changes to behaviour (see Chapters 4 and 5). Simulated lower visual field loss was associated with lowered head pitch angles, raised eye angles (see Chapters 4 and 5) as well as a reduced number of fixations and a more asymmetric gait (Chapter 5 only). However, effect sizes and the scales of change were general smaller than environmental factors. Moreover, simulated reduced cognitive capacity did not produce any meaningful changes in gaze or gait. This may suggest that surface complexity (or extrinsic factors in general) are of greater fall risk than the intrinsic factors tested here. More likely, the young participants tested were able to cope well with the additional simulated deficits, both separately and in combination. Our findings are in contrast to those that have simulated these deficits in young people for laboratory conditions (Graci, Elliott, & Buckley, 2010; Marigold & Patla, 2008; Plummer-D'Amato, et al., 2012; Yamada, et al., 2011). However, as our studies were primarily conducted outdoors, we speculate that environmental factors associated with this more complex and varied setting might explain our different findings. Testing outdoors is often accompanied by uncontrollable variance-inducing influences from pedestrians and traffic, producing visual and auditory distractions. The effect of these environmental challenges may mask any behavioural changes shown from our relatively limited simulations of intrinsic factors. This would explain other inconsistencies in the literature in comparing gait and cognitive load between laboratory and real-world testing (for example see Ellmers, Cocks, Doumas, Williams, & Young, 2016; Feld & Plummer, 2019). If this is indeed the case, the results of previous studies that have simulated intrinsic factors indoors may be invalid outdoors because of environmental differences. In this case, conclusions from such studies should be limited to their environmental settings only. Furthermore, when assessing the impact of intrinsic factors, we recommend that research should be carried out on directly affected populations, not by simulating the factors in the young. Experiments should also be carried out in the appropriate environmental context.

7.1.2 Perception as a measure for surface complexity

The second main conclusion from the thesis was the development of a potential metric for surface complexity in the form of perceptual ratings. We showed that perception ratings are an effective, simple measure that can predict behavioural change (Chapter 3) and further showed that surface perception does not differ with age or experience (Chapter 6).

From conducting our first study (Chapter 2), we found that it was difficult to make predictions related to stability for surfaces used within our study based on those used by others. As there were no suitable existing metrics whereby to compare such different surface conditions, we proposed a new method. This method consisted of using a combination of several physical and perceptual measures of surfaces (Chapter 3). In doing so, to our knowledge, we are the only researchers who have objectively defined surfaces based on their complexity. This method showed perceptual and most physical measures to be highly correlated and, crucially, found that these measures could act as a proxy for behavioural change indicative of stability. In particular, we were interested in comparing surfaces on the basis of perceptual measures, given the simplicity and ease of collecting this data. This measure would be of interest to researchers who wanted to test environmental settings for potential fall risk before collecting behavioural data. For our other studies (Chapters 4 and 5) we used perceptual measures to compare the complexity of different surfaces used. This measure proved insightful given that surfaces perceived as more complex consistently caused greater behavioural changes, indicative of instability, across both studies.

As well as the efficacy of perception as a measure of surface complexity, we were interested in whether surface complexity perception changed depending on age and experience. Changing perception with ageing was of interest given the higher incidence of injurious falls in older people when walking over more complex surfaces (Li, et al., 2006). Despite the possibility that a difference in perception of more complex surfaces in older people increases fall risk, we found that older people perceived surfaces similarly to the young consistently across all surface types. This may suggest that older people, unfortunately, do not take into consideration their relative capabilities compared to the young when rating surface complexity. This error might well itself explain the greater fall risk with age. Alternatively, similar surface perception ratings between older and young people may result from older people adopting a more cautious gait across all settings. Given the existing methods deployed for public walkway maintenance by councils, we also wished to determine whether experience of surface perception was a pertinent factor. Current procedures in the UK for gathering data relevant to the decisions on the need for surface repair or replacement typically rely on a single individual's perception of the surface, completed irregularly and in person (for example see Surrey County Council, 2008). We showed that tests of the efficacy of viewing single surface images online gave comparable results to those given first-hand. Given these findings, decisions in respect to pavement maintenance may be completed by councils more easily, performed remotely and by multiple people. If this result was taken into consideration by councils, more complex surfaces could be replaced and repaired more frequently, which should reduce incidences of falls from these locations.

7.2 Limitations and future research

The research carried out in this thesis furthers our understanding of gaze and gait behaviour when outdoors, specifically in relation to how extrinsic and intrinsic factors affect stability. However, this body of work does include some limitations which should be addressed in future research.

From our research, we showed that extrinsic and, to a lesser extent, intrinsic factors changed gaze and gait behaviour. Behavioural changes were primarily determined from differences in mean values between different conditions. However, we did not determine precisely how different conditions affect behaviours on a step to step basis. We did manage to determine such behavioural changes for one study (see Chapter 5), but, high variability in the recorded data only allowed for a small number of meaningful comparisons. Outdoor studies are known to show greater variance in behavioural measures of gait than those in the laboratory (Tamburini, et al., 2018; Toda, Maruyama, & Tada, 2020). Although we controlled for gross variability within our studies (including lighting, time of day, weather and surface friction), given that we primarily used public walkways we could not control for all variability found outdoors. Furthermore, participants typically walked only once for each condition on each surface. Therefore, less data was available for each condition, so that unpredictable attentional factors (e.g. police sirens, sudden slips) would likely cause increased variance. The reason for only one walk per condition was due to the practical issues brought about by the limited battery life of the sensors, whilst participants were required to traverse multiple surfaces for many conditions. Indeed, limited sensor battery life caused a notable proportion of the data for one study (see Chapter 5) to have to remain unused. In determining conditions for a large range of surfaces and completing studies under relatively uncontrolled settings, our approach was efficacious in emulating those conditions experienced when walking in everyday life. However, future research should aim to assess behaviour over a smaller number of surfaces numerous times to show whether extrinsic or intrinsic factors cause any step to step behavioural responses.

For our studies, we primarily focused on assessing behavioural changes for young participants. Young participants were used given the limited number of any other studies assessing gaze and gait behaviour when walking outdoors (for example 't Hart & Einhauser, 2012; Matthis, Yates, & Hayhoe, 2018; Tomasi, Pundlik, Bowers, Peli, & Luo, 2016) and to prevent confounding factors from age-related comorbidities. Furthermore, one aim of the study was to show how a single and, later, a second intrinsic factor affected behaviour when walking. It would be implausible to conduct such studies on older participants given that existing age-related comorbidities may affect such results. Moreover, some of the surfaces to be traversed were considered to be very complex by young participants and therefore would likely have led to high risk of an injurious fall if walked over by older participants. Our own study showed that older participants perceived surfaces similarly to the young (Chapter 6), which may indicate that older people underestimate their risk of a fall. However, our research (Chapters 4 and 5) also showed that simulating age-related intrinsic factors in the young is potentially impractical as they were still able to cope with such deficits. As such, future studies should aim to determine how older people's behaviour changes under the conditions tested here in order to determine fall risk factors consistently. The difficulties in conducting any such study would be in balancing the assessment of behaviour outdoors (under conditions deemed to be of high fall risk and thus of high validity), whilst also ensuring older participants were safe when undertaking the procedures required of them.

Within almost all chapters, we assessed multiple behavioural measures as an indicator for stability and predictor for fall risk. Whilst it is reasonable to assume that behavioural measures related to stability are associated with the occurrence of falls, it must be acknowledged that falls have a multi-factorial aetiology and a comprehensive, prospective falls study is needed to explore their merit in predicting falls. Conducting any such study would have multiple challenges, one being the difficulty to measure falls longitudinally, i.e. the accuracy of self-reported falls are typically low due to difficulties with accurate recall in older adults (Freiberger & de Vreede, 2011), and that sensor-based approaches have high false-positive rates (see for example (Broadley, Klenk, Thies, Kenney, & Granat, 2018). Furthermore, falls occur relatively rarely and as such, determining behaviour change associated with falls is complex without longitudinal data. One potential method to determine accurate fall numbers and location settings within a set time could be through the utilisation of CCTV, although any such study would likely be limited to more public spaces. Alternatively, advancements in wearable technology could allow for more accurate assessments of falls in future studies whilst also being used to determine which behavioural changes over time are most associated with fall risk.

7.3 Conclusion

In conclusion, I have shown in this thesis that gaze and gait behaviours can be used to indicate stability whilst walking outdoors. In particular, I have shown that extrinsic factors (especially when more challenging) affect behaviour, whilst young participants can cope well with simulations of common age-related intrinsic factors. These findings suggest that environmental factors are a common fall risk. However, separating age-related intrinsic factors and attempting to simulate them are both ineffective and should be avoided outdoors. In the second major component, I developed a stability metric that is an effective proxy for behaviour. This measure could be used to predict behavioural responses over a wide range of surface conditions.

In combination, the findings of these two components serve as a foundation for future research seeking to determine stability outdoors. I recommend that outdoor research should be population-specific, but note that perceptual measures may act as a simple measure whereby to predict expected behavioural changes. If these recommendations are adopted in future research, I can further tease apart those factors most important in destabilising behaviour, and ultimately use this knowledge to reduce fall risk.

7.4 References

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