Probability of Lateral Instability While Walking on Winding Paths

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest associated with this work.

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ABSTRACT

People with balance impairments often struggle performing turns or lateral maneuvers, which can increase risk of falls and injuries. Here we asked how people maintain mediolateral balance when walking on non-straight winding paths. Twenty-four healthy adults (12F/12M; 25.8±3.5 yrs) participated. Each walked on each of six paths projected onto a treadmill, comprised of three pseudo-random path oscillation frequency combinations (straight, slowly-winding, quickly-winding), each presented at either wide or narrow width. We quantified stepping errors as the percent of steps taken off each path. We quantified minimum mediolateral Margin of Stability (MoS_L) at each step and calculated means (μ) and standard deviations (σ) for each trial. We calculated lateral Probability of Instability (PoI_L) as participants' statistical risk of taking unstable ($MoS_L < 0$) steps. On *narrower* paths, participants made more stepping errors on the winding paths ($p < 0.001$) and walked with smaller $\mu(MoS_L)$ on all paths ($p < 0.001$), but exhibited significantly increased PoI_L only on the slowly-winding path ($p < 0.001$). On *windy* paths, participants made increasingly more stepping errors ($p < 0.001$) for increasingly windier narrow paths ($p < 0.001$). They consistently walked with smaller $\mu(MoS_L)$, larger $\sigma(MoS_L)$, and increased PoI_L on increasingly windier paths of both widths (all $p < 0.001$). Though many took numerous unstable steps, no participant *fell*. Our results demonstrate healthy adults' ability both to trade off increased risk of lateral instability for greater maneuverability, and to employ highly-versatile stepping strategies to still maintain balance while walking.

INTRODUCTION

Maneuvering constitutes a significant proportion of daily activities (Glaister et al., 2007). Walking around corners (Bergsma et al., 2021; Tillman et al., 2022), in crowded environments (Degond et al., 2013), through narrow spaces, or negotiating obstacles (Musselman and Yang, 2007) are fundamental to our mobility. However, executing maneuvers imposes that we adapt our stepping (Desmet et al., 2022; Hak et al., 2013; Ochs et al., 2021; Twardzik et al., 2019). Such tasks may heighten our risk of instability (Bruijn and van Dieën, 2018; Desmet et al., 2022; Desmet et al., 2024), particularly as people age and face challenges in weight shifting (Patla et al., 1993) and balance control (van Dieën et al., 2005). Indeed, older adults often fall when trying to perform such lateral maneuvers (Robinovitch et al., 2013). This poses potential for serious injury (Parkkari et al., 1999; Yang et al., 2020). Thus, it is important to better understand how executing lateral maneuvers affects mediolateral balance while walking.

One metric widely used to quantify walking balance is the lateral margin of stability (MoS_L) (Hof, 2008). MoS_L quantifies a *margin* as the linear distance from a *threshold* (i.e., $MoS_L = 0$) beyond which stability is presumed to be compromised (Hof et al., 2005; Kazanski et al., 2024). However, in multiple *de*stabilizing contexts, people exhibit larger (not smaller) mean values of MoS_L (Hak et al., 2012; Hurt and Grabiner, 2015; Onushko et al., 2019; Wu et al., 2017). Such larger mean MoS_L are often interpreted to indicate greater stability (Watson et al., 2021), which is quite counterintuitive. This arises because interpreting mean MoS_L values as indicating stability runs contrary to MoS_L's definition as a *margin*. We proposed a different statistic, lateral Probability of Instability (PoI_L) (Kazanski et al., 2022), computed from the same MoS_L values as the mean, but consistent with Hof's original definition. PoI_L resolves the paradox of misinterpreting mean MoS_L (Kazanski et al., 2022), and explains why perturbed/impaired people take wider steps to maintain balance (Dean et al., 2007). When people can readily take wider steps, doing so will *increase* their mean MoS_L. But when this offsets greater step-to-step variability of MoS_L (McAndrew Young et al., 2012; Onushko et al., 2019), it can simultaneously *decrease* PoI_L (Kazanski et al., 2024).

However, most often when people walk, they follow paths with lateral boundaries that restrict where they can step (Dingwell and Cusumano, 2019; Kazanski et al., 2023). These paths sometimes have well-defined boundaries, like hallways, sidewalks, etc., or sometimes less-well-defined boundaries, like outdoor walking trails (Matthis et al.,

2018), etc. Such lateral path boundaries limit people's stepping options for maintaining balance. Thus, when people walk on narrow paths or beams, they exhibit smaller mean MoS_L (Arvin et al., 2016; da Silva Costa et al., 2020; Kazanski et al., 2024; Schrager et al., 2008).

Similarly, when people make discrete turns or maneuvers, MoS_L typically decreases on so-called "inside" steps (where the stepping foot is ipsilateral to direction of the maneuver) and increases on so-called "outside" steps (where the stepping foot is contralateral to the direction of the maneuver) (Acasio et al., 2017; He et al., 2018; Ho et al., 2023; Wu et al., 2015). The smaller MoS_L on inside steps implies that people are more unbalanced in the direction of the maneuver. This, however, simultaneously facilitates their ability to execute that maneuver (Desmet et al., 2022). Hence, people trade-off compromising their stability to enhance their lateral maneuverability (Acasio et al., 2017; Desmet et al., 2022).

Real-world paths are often both laterally constrained *and* non-straight (Bergsma et al., 2021; Matthis et al., 2018; Moussaïd et al., 2011). Experiments have not yet assessed how these competing factors combine to affect MoS_L. Therefore, to simulate real-world-like walking conditions that impose continuously-changing balance challenges, here we created winding walking paths. We investigated the influence of these paths' lateral oscillation frequency, or sinuosity, by creating paths with either slowly-winding or quickly-winding curves. We also tested the influence of path width by creating wide and narrow versions of each winding path.

We hypothesized that people walking on narrow paths would take more unstable steps due to the constraints placed on foot placement. We hypothesized that people walking on windier (i.e., higher sinuosity) paths would likewise take more unstable steps due to their continuously changing direction. Lastly, we hypothesized that each of these two factors (path width and sinuosity) would compound each other, such that people would take even more unstable steps when both challenges were imposed simultaneously.

By investigating how varying degrees of continuous maneuvering affect one's probability of experiencing lateral balance loss, we further and better characterize how people make trade-offs between stability and maneuverability (Acasio et al., 2017; Desmet et al., 2022; Wu et al., 2017). This research holds particular significance for high fall-risk populations like older adults (Robinovitch et al., 2013), as it offers insights into identifying everyday tasks that may impose a challenge to their stability. By quantifying risk of lateral instability, this work both expands our understanding of human locomotion and contributes to developing strategies aimed at enhancing mobility and mitigating fall risk in diverse populations.

METHODS

Participants

Prior to participation, twenty-four participants (Table 1) provided written informed consent, as approved by the Institutional Review Board of Penn State University. Participants were screened to ensure no medications, lower limb injuries, surgeries, musculoskeletal, cardiovascular, neurological, or visual conditions affected their gait.

[Insert Table 1 About Here]

Experimental Protocol

Participants walked on a 1.2 m wide treadmill in an M-Gait virtual reality system (Motek Medical, Netherlands; Fig.1A). Each participant wore a safety harness. All walking trials were performed at 1.2 m/s. Participants first walked 4-minutes to acclimate to the system.

Participants were asked to walk on paths projected onto the treadmill belt (Fig. 1A). We created these paths using

a sum of sin waves:

$$z(x) = 0.22\sin(A \cdot 0.46875x) + 0.05\sin(A \cdot 0.625x) + 0.03\sin(A \cdot 0.9375x), \quad (1)$$

where z is the lateral position (in meters) of the path center, x is forward distance (in meters), and A is a frequency scaling factor. Each participant walked on each of six unique paths (Fig. 1B), combining either of two path widths, wide (W = 0.60 m) and narrow (N = 0.30 m), with each of three oscillation frequencies: straight (STR: $A = 0$), low frequency (LOF: $A = 1$), and high frequency (HIF: $A = 4$).

We instructed participants to "stay on the path" and minimize stepping errors. They received visual (firework) and auditory (flute) penalties when steps landed outside the path boundaries. For each condition, participants completed a 1-minute introductory trial followed by two 4-minute experimental trials. Order of presentation of conditions was randomly assigned to each participant and counterbalanced across participants using a Latin Square design. Participants were allowed to rest as needed after each trial.

[Insert Figure 1 About Here]

Data Processing

Each participant wore 16 retroreflective markers: four around the head, four around the pelvis (left and right PSIS and ASIS), and four on each shoe (first and fifth metatarsal heads, lateral malleolus, and calcaneus). Kinematic data were collected at 100 Hz from a 10-camera Vicon system (Oxford Metrics, Oxford, UK) and post-processed using Vicon Nexus software. Marker trajectories and path data from D-Flow software (Motek Medical, Netherlands) were analyzed in MATLAB (MathWorks, Natick, MA).

For each experimental trial, we low-pass filtered (10 Hz 4th-order Butterworth) the raw marker trajectories and interpolated these data to 600 Hz (Bohnsack-McLagan et al., 2016). Heel strikes and toe-offs were identified using a previously validated algorithm (Zeni et al., 2008). For consistency, we analyzed the last $N = 300$ steps of each trial.

On a curved path, one's direction of motion changes at each new step. We therefore transformed our data into path-based local coordinates (Dingwell et al., 2023; Ho et al., 2023). At each step, we aligned this path-based local coordinate system to be tangent to the point on the path closest to the midpoint between the left and right foot placements for that step (Dingwell et al., 2023). The locally lateral (z-axis) motion was then taken to be perpendicular to the path at that point on the path.

Stepping Errors

The instructed task objective was to remain on the path. We therefore quantified Stepping Errors as the percentage of steps (out of $N = 300$) within each trial that landed outside the path's boundaries. This measure served as a functional measure of overall task performance.

Lateral Margins of Stability

We quantified lateral stability in the locally-lateral z-direction at each step (Fig. 2A). We took the average motion of the 4 pelvis markers to approximate the center-of-mass (CoM) state ($z, \dot{z}$) (Havens et al., 2018). The extrapolated center-of-mass (*XCoM*) position was then (Hof et al., 2005):

$$XCoM = z + \frac{\dot{z}}{\omega_0}, \quad (2)$$

where $\omega_o = \sqrt{(9.81\, m/s^2)/(1.34 \cdot l)}$ and l was leg length (Hof et al., 2005). We took the z-position of the leading foot's fifth metatarsal-phalangeal joint marker to approximate the lateral boundary of the base of support (u_{max}). We calculated the *minimum* MoS_L within each step n as:

$$MoS_{L_{min}} = \min\,(u_{max} - XCoM)_n. \tag{3}$$

Hence, a positive MoS_{Lmin} indicated a stable step, while a negative MoS_{Lmin} indicated an unstable step.

For each trial performed by each participant for each condition, we extracted time series of MoS_{Lmin} (e.g., Fig. 2B) from all $n \in \{1, \ldots, 300\}$ steps. We then computed the within-trial means, $\mu(MoS_{Lmin})$, and standard deviations, $\sigma(MoS_{Lmin})$, for each trial.

[Insert Figure 2 About Here]

Lateral Probability of Instability

As defined (Hof et al., 2005), MoS_L is a *margin* that quantifies the distance to a defined *threshold* for becoming unstable (i.e., $MoS_L = 0$). While researchers commonly average MoS_L across steps in a trial (Watson et al., 2021), this is *not* consistent with MoS_L being a margin (Kazanski et al., 2022, 2024), because $\mu(MoS_L)$ does not quantify a person's risk of exceeding that threshold (i.e., of experiencing $MoS_L < 0$).

Therefore, for each trial, we estimated the lateral *Probability of Instability* (PoI_L) (Kazanski et al., 2022) as the cumulative probability (P), for an assumed normal distribution of MoS_{Lmin}, that steps within that trial would exceed the $MoS_{Lmin} < 0$ threshold (Fig. 2C):

$$PoI_L = P(MoS_{Lmin} < 0) = \frac{1}{2}\left[1 - erf\left(\frac{\mu\left(MoS_{L_{min}}\right)}{\sigma\left(MoS_{L_{min}}\right)} \cdot \frac{1}{\sqrt{2}}\right)\right] \times 100\%. \tag{4}$$

For example, a $PoI_L = 10\%$ would suggest a person was likely to take ~30 unstable ($MoS_{Lmin} < 0$) steps over a 300 step trial. Importantly, PoI_L is neither "new" or "different": it simply extracts a different statistical metric than the mean from the exact same distribution of MoS_{Lmin} values (Fig. 2B-C).

Statistical Analyses

We applied a two-factor (Frequency × Width) mixed-effects analyses of variance (ANOVA) with repeated measures to test for differences between conditions for each dependent measure: % Stepping Errors, $\mu(MoS_{Lmin})$, $\sigma(MoS_{Lmin})$ and PoI_L. For $\sigma(MoS_{Lmin})$, to satisfy normality assumptions, we first log-transformed these data. For PoI_L, because multiple trials yielded $PoI_L = 0$, we first added a small constant value (0.001) before we log-transformed PoI_L. When we found main or interaction effects to be significant, we performed Tukey's pairwise post-hoc comparisons to test for specific differences between path frequencies (STR, LOF, HIF) for each path width (W, N), and between path widths for each path frequency. All statistical analyses were conducted using Minitab (Minitab, Inc., State College, PA).

RESULTS

Stepping Errors

Path width did not influence the number of stepping errors (Fig. 3) on the STR path ($p = 0.253$; Table 2). However, participants took more steps off the narrower paths than the wide paths for both LOF and HIF ($p < 0.001$; Fig. 3;

Table 2). Similarly, participants made more stepping errors as path oscillation frequency increased (from STR to LOF to HIF) for all narrow paths (all $p \leq 0.007$), but not for the wide paths (all $p > 0.94$) (Fig. 3; Table 2).

[Insert Figure 3 About Here]
[Insert Table 2 About Here]

Lateral Margins of Stability

Qualitatively, step-to-step time series of MoS_{Lmin} exhibited increasingly larger-amplitude fluctuations from the STR paths to LOF paths, and much larger still from the LOF paths to HIF paths (Fig. 4).

[Insert Figure 4 About Here]

People exhibited smaller means, $\mu(MoS_{Lmin})$, on paths of both narrower width ($p < 0.001$) and increased oscillation frequency (all $p < 0.001$; Fig. 5A; Table 2). People exhibited greater variance, $\sigma(MoS_{Lmin})$, on the Narrow vs. the Wide HIF path ($p < 0.01$; Fig. 5B; Table 2), but similar variance for both path widths for both STR ($p = 0.107$) and LOF ($p = 0.999$). People also exhibited increased $\sigma(MoS_{Lmin})$ with increased path sinuosity (from STR to LOF to HIF), regardless of path width (all $p < 0.001$; Fig. 5B; Table 2).

[Insert Figure 5 About Here]

Lateral Probability of Instability

For each trial, that trial's mean, $\mu(MoS_{Lmin})$ (Fig. 5A), and standard deviation, $\sigma(MoS_{Lmin})$ (Fig. 5B), were used to compute that trial's PoI_L (Eq. 4) (Fig. 6). People exhibited a higher PoI_L ($p < 0.001$) on the narrower LOF path compared to the wide LOF path (Fig. 6; Table 2), but similar PoI_L at both path widths for both STR ($P = 0.208$) and HIF ($p = 0.997$).

For both path widths individually, people exhibited very low PoI_L on the STR paths, slightly but significantly ($p < 0.001$) higher PoI_L on the LOF paths, and *much* higher PoI_L on the HIF paths (all $p < 0.001$) (Fig. 6). Pooled across both path widths, participants' mean probability of taking unstable steps on the STR paths was only $PoI_L \approx 0.06\%$ (range [0%, 2.87%]). This equates to taking 1 unstable step every ~1,688 steps (range [∞, ~35] steps). On the LOF paths, these increased to mean $PoI_L \approx 0.56\%$ (range [0%, 5.37%]), or 1 unstable step every ~180 (range [∞, ~19]) steps. On the HIF paths, these increased to mean $PoI_L \approx 45.8\%$ (range [~30.9%, ~58.5%]), or 1 unstable step every ~2.2 (range [~3.2, ~1.7]) steps. Thus, the HIF paths in particular *substantially* disrupted people's ability to maintain stable walking (e.g., as seen in Fig. 4).

[Insert Figure 6 About Here]

DISCUSSION

Everyday walking often entails navigating crowded and/or non-straight paths (Bergsma et al., 2021; Degond et al., 2013; Glaister et al., 2007). These tasks require people to adapt their stepping to precisely maneuver (Acasio et al., 2017; Wu et al., 2015). However, this maneuverability can increase one's risk of experiencing instability (Desmet et al., 2024; Tillman et al., 2022). Many older adults fall because they cannot adequately negotiate such non-straight walking tasks (Robinovitch et al., 2013). Despite their prevalence, we know little about how path width and/or shape affect lateral stability during walking. This study therefore examined real-world-like walking on winding paths of varying sinuosity and width. The results reveal how such tasks challenge people's ability to maintain lateral balance while walking.

Our first hypothesis, that people would take more unstable steps when walking on *narrow* paths was partly supported. On the Narrow paths, participants made more stepping errors for LOF and HIF paths (Fig. 3), walked with smaller mean MoS_{Lmin} on all three path types (Fig. 5A), more variable MoS_{Lmin} on HIF paths (Fig. 5B), and exhibited significantly increased instability risk on the Narrow LOF path (Fig. 6). Our second hypothesis, that people would take more unstable steps on windier paths was very strongly supported. Participants made increasingly more stepping errors from STR to LOF to HIF paths, walked with both smaller mean MoS_{Lmin} (Fig. 5A) and more variable MoS_{Lmin} (Fig. 5B) from STR to LOF to HIF paths, and most importantly, exhibited significantly increased instability risk from STR to LOF to HIF paths (Fig. 6). Our third hypothesis that simultaneously narrow and windier paths would further exacerbate participant's ability to maintain balance was also supported. People did not make more stepping errors with increased path sinuosity on Wide paths, but did on Narrow paths (Fig. 3). For $\sigma(MoS_{Lmin})$ and PoI_L, path width differences not observed for STR paths, became significant (Table 2) on HIF (Fig. 5B) and LOF (Fig. 6) paths, respectively.

On the Narrow paths, the only consistent difference observed across all sinuosity conditions was that people walked with significantly smaller mean MoS_{Lmin} (Fig. 5A; Table 2). This was most likely because they needed to adopt narrower step widths (Arvin et al., 2016; Kazanski et al., 2024; McAndrew Young and Dingwell, 2012; Schrager et al., 2008). However, despite these smaller $\mu(MoS_{Lmin})$, which would typically be interpreted as indicating greater instability (Watson et al., 2021), we did not observe corresponding changes in people's probability to take unstable steps (Fig. 6). From the Wide to Narrow LOF paths, participants did exhibit significant ($p < 0.001$), but modest increases in PoI_L, from 0.34% to 0.76% (i.e., from taking an unstable step once every ~294 steps to once every ~132 steps). However, they exhibited *no* significant increases in PoI_L from the Wide to Narrow paths for STR ($p = 0.208$) or HIF ($p = 0.997$; Table 2). These results further support prior findings (Kazanski et al., 2022, 2024) that measures of $\mu(MoS_{Lmin})$, despite their prevalence (Watson et al., 2021), do *not* quantify risk of taking unstable steps, whereas PoI_L does (Fig. 2C).

On the winding paths (LOF & HIF), participants took more unstable ($MoS_{Lmin} < 0$) steps, especially on the HIF paths, where participants took unstable steps as often as once every ~2-3 steps (Figs. 4 & 6). By comparison, in a prior experiment, we subjected young and older adults to unpredictable lateral physical perturbations (Kazanski et al., 2022). Those perturbations only induced, on average, $PoI_L < \sim 3\%$ (range [0%, ~21%]), or 1 unstable step every ~33 (range [∞, ~5]) steps ((Kazanski et al., 2022); Fig. 8B). Hence, walking on winding paths appears potentially far more laterally destabilizing than physically perturbing people. This may seem surprising given that, in the current experiment, participants experienced *no* external perturbations and were given full visual information about their path well in advance to plan their foot placements (Matthis et al., 2017). However, unlike in (Kazanski et al., 2022) where participants could step where they chose, participants here were instructed to keep their feet *on their paths*. This constrained where they could take their next step, which most likely accounts for their increased instability (Bruijn and van Dieën, 2018).

For HIF trials, MoS_{Lmin} time series (Fig. 4) appeared potentially skewed. Since Eq. (4) estimates PoI_L assuming a Gaussian distribution (Fig. 2C), we computed the skewness of each MoS_{Lmin} timeseries. We then also calculated the actual percentage of unstable $MoS_{Lmin} < 0$ steps taken within each trial, and correlated these against our PoI_L estimates. While STR and LOF trials were mostly minimally skewed, most HIF trials were moderately negatively skewed (Fig. 7A). Correspondingly, PoI_L predicted % unstable steps well for both STR and LOF, but somewhat overestimated % unstable steps for HIF (Fig. 7B). Hence, assuming normality somewhat limited the accuracy of our PoI_L predictions for the HIF trials.

[Insert Figure 7 About Here]

Importantly however, these differences in no way change our conclusions here, given the very large PoI_L for HIF compared to STR and LOF (Fig. 6). Future studies should check for skewness in their MoS_{Lmin} data before estimating PoI_L. In some contexts, it might be more appropriate to directly calculate the percent of unstable ($MoS_{Lmin} < 0$) steps taken, such as when sample sizes are large (i.e., many steps per trial) and/or instability risk is high (e.g., as in HIF trials here). However, in contexts where long trials are not feasible and/or instability risk is low/moderate (e.g., as in STR or LOF trials here), one may not observe enough unstable steps to get good direct estimates, and Eq. (4) may be preferrable. Alternatively, one could modify Eq. (4) to incorporate skewness in addition to mean and standard deviation.

Despite participants' clearly taking numerous unstable steps (Fig. 4 & 6), *no participant fell*. Taking a step with $MoS_{Ln} < 0$ does not necessitate failure (Gill et al., 2019) – but instead, only that one must use strategies to regain balance that are *not* available to an inverted pendulum (Hof et al., 2005; Kazanski et al., 2022). The primary strategy is to take a *step* (Redfern and Schumann, 1994; Townsend, 1985). Even simple bipeds generally can choose among infinite stepping options to minimally remain "viable" (i.e., "not fall") (Patil et al., 2022; Zaytsev et al., 2018), and switching stepping goals at each step can, in principle, allow them to walk effectively forever (Patil et al., 2022). Humans use such strategies when they make discrete maneuvers (Desmet et al., 2022). Moreover, viability gives rise to "*semi*stability", which allows expansive versatility of walking that is both viable and purposeful (Patil et al., 2024). That participants here took so many unstable steps (e.g., Fig. 4) without falling strongly suggests they employ such highly-versatile stepping strategies to continuously trade off stability for maneuverability (Acasio et al., 2017) at each step.

Here, continuously winding paths compromised participant's stability, demonstrating how people trade off stability for maneuverability. The increased likelihood for people taking an unstable step on these winding paths emphasizes the importance of individuals being able to frequently and successfully enact mechanisms to regain their balance and mitigate falls in destabilizing contexts. To improve everyday mobility in at-risk populations, interventions can target strategies, such as stepping adjustments or weight shifting, that enable people to quickly and effectively respond to balance disturbances.

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TABLES & FIGURES:

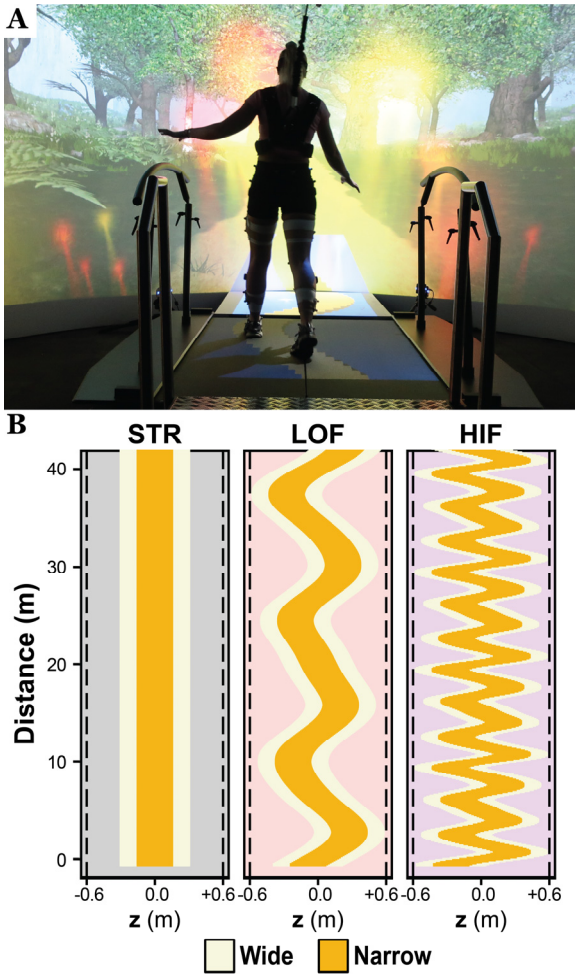
Table 1. Participant characteristics. All values except Sex are given as Mean ± Standard Deviation.

Characteristic:	Value:
Sex [F/M]	12 / 12
Age [yrs]	25.8 ± 3.5
Body Height [m]	1.74 ± 0.11
Body Mass [kg]	70.15 ± 14.75
Leg Length [m]	0.93 ± 0.05

Table 2. Statistical results for differences between path Frequencies (STR, LOF, and HIF) and path Widths (Wide, Narrow) for the data shown in Figs. 3, 5 and 6, including: step errors, means (μ) and variability (σ) for Margin of Stability (MoS_L), and Probability of Instability (PoI_L). ANOVA results (F-statistics and p-values) are provided for main effects of Frequency, Width, and Frequency×Width. In cases where Frequency×Width interactions were significant, we considered main effects results (marked 'p*') to be unreliable. We drew conclusions instead from the Tukey's pairwise comparisons, as these account for the effects of the interactions. Significant differences are indicated in bold.

Data In	Variable	Frequency	Width	Frequency × Width	Tukey's (Frequency Effects)	Tukey's (Width Effects)
Fig. 3:	Step Errors	$F_{(2,259)} = 117.81$ $p^* < 0.001$	$F_{(1,259)} = 270.36$ $p^* = < 0.001$	$F_{(2,259)} = 96.79$ **$p < 0.001$**	STRW-LOFW: $p = 1.000$ STRW-HIFW: $p = 0.943$ LOFW-HIFW: $p = 0.947$ **STRN-LOFN: $p = 0.007$** **STRN-HIFN: $p < 0.001$** **LOFN-HIFN: $p < 0.001$**	STRW-STRN: $p = 0.253$ **LOFW-LOFN: $p < 0.001$** **HIFW-HIFN: $p < 0.001$**
Fig. 5A:	$\mu(MoS_L)$	$F_{(2,261)} = 2{,}682.41$ **$p < 0.001$**	$F_{(1,261)} = 364.16$ **$p < 0.001$**	$F_{(2,259)} = 1.92$ $p = 0.149$	**STR-LOF: $p < 0.001$** **STR-HIF: $p < 0.001$** **LOF-HIF: $p < 0.001$**	**N/A**
Fig. 5B:	$\ln(\sigma(MoS_L))$	$F_{(2,259)} = 5{,}596.69$ $p^* < 0.001$	$F_{(1,259)} = 0.81$ $p = 0.368$	$F_{(2,259)} = 9.98$ **$p < 0.001$**	**STRW-LOFW: $p < 0.001$** **STRW-HIFW: $p < 0.001$** **LOFW-HIFW: $p < 0.001$** **STRN-LOFN: $p < 0.001$** **STRN-HIFN: $p < 0.001$** **LOFN-HIFN: $p < 0.001$**	STRW-STRN: $p = 0.107$ LOFW-LOFN: $p = 0.999$ **HIFW-HIFN: $p = 0.003$**
Fig. 6:	$\ln(PoI_L + 0.001)$	$F_{(2,259)} = 1{,}415.23$ $p^* < 0.001$	$F_{(1,259)} = 39.75$ $p^* < 0.001$	$F_{(2,259)} = 16.29$ **$p = < 0.001$**	**STRW-LOFW: $p < 0.001$** **STRW-HIFW: $p < 0.001$** **LOFW-HIFW: $p < 0.001$** **STRN-LOFN: $p < 0.001$** **STRN-HIFN: $p < 0.001$** **LOFN-HIFN: $p < 0.001$**	STRW-STRN: $p = 0.208$ **LOFW-LOFN: $p < 0.001$** HIFW-HIFN: $p = 0.997$

Figure 1. A) Photo of a participant walking in the Motek M-Gait virtual reality system with a path projected onto the treadmill surface. **B)** Participants traversed paths of each of three oscillation frequency combinations (Eq. 1): straight (STR; grey panel), low frequency (LOF; red panel), and high frequency (HIF; purple panel). Each path frequency was presented at each of two different path widths, wide (W = 0.6m; beige) and narrow (N = 0.3m; yellow), for a total of six unique conditions.



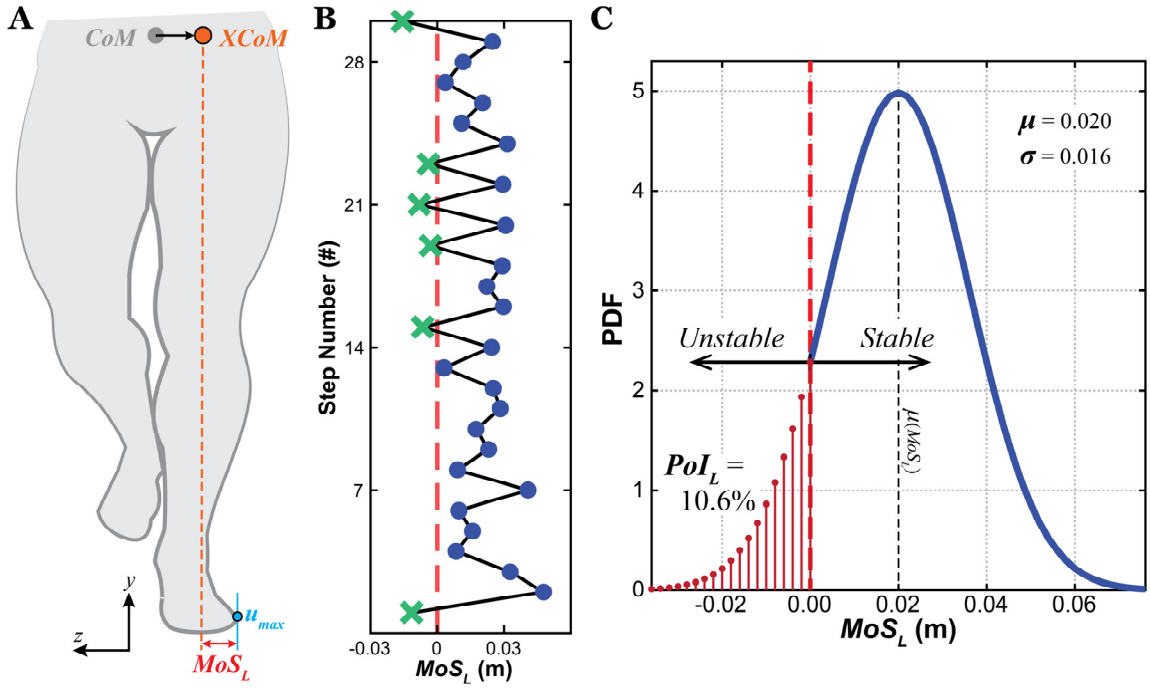
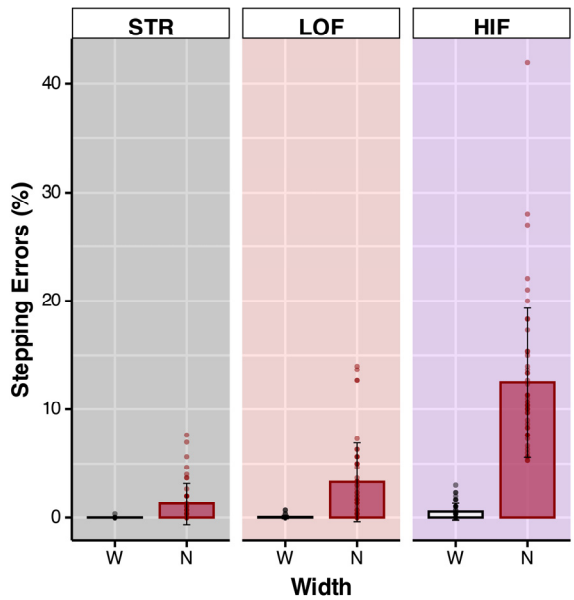


Figure 2. A) Schematic showing the relevant variables extracted at each step to calculate MoS_{Lmin} (Eq. 2-3): center-of-mass (CoM; grey), extrapolated center-of-mass ($XCoM_L$; orange), and lateral base-of-support boundary (u_{max}; blue). **B**) Example time series data of MoS_{Lmin} across several steps. The vertical red dashed line indicates $MoS_{Lmin} = 0$. Values of $MoS_{Lmin} > 0$ (blue ● markers) are considered stable, while values of $MoS_{Lmin} < 0$ (green × markers) are considered unstable. **C**) Hypothetical probability density function (PDF) to demonstrate how to calculate PoI_L from a distribution of MoS_{Lmin} values (e.g., as might be obtained from **B**, etc.). Here, $\mu(MoS_{Lmin}) = 0.020$ and $\sigma(MoS_{Lmin}) = 0.016$. The dashed vertical red line indicates the stability threshold separating stable ($MoS_{Lmin} > 0$) from unstable steps ($MoS_{Lmin} < 0$). Note that the mean, $\mu(MoS_{Lmin}) = 0.020$, is well within the *stable* region, and so yields no information regarding *un*stable steps. Conversely, PoI_L (Eq. 4) directly calculates the cumulative probability (area under the curve) precisely of those *un*stable ($MoS_{Lmin} < 0$) steps. Here $PoI_L = 10.6\%$, which equates to taking 1 unstable step every ~9.4 steps. Thus, PoI_L directly estimates statistical *risk* of instability, consistent with Hof's theory, while $\mu(MoS_{Ln})$ does not.

Figure 3. Percent stepping errors on the wide (W) and narrow (N) paths for each path oscillation frequency: STR (grey), LOF (red), and HIF (purple). Bar plots represent the mean values. The overlaid markers are individual data points for each trial for each participant. Results of statistical analyses are detailed in Table 2.



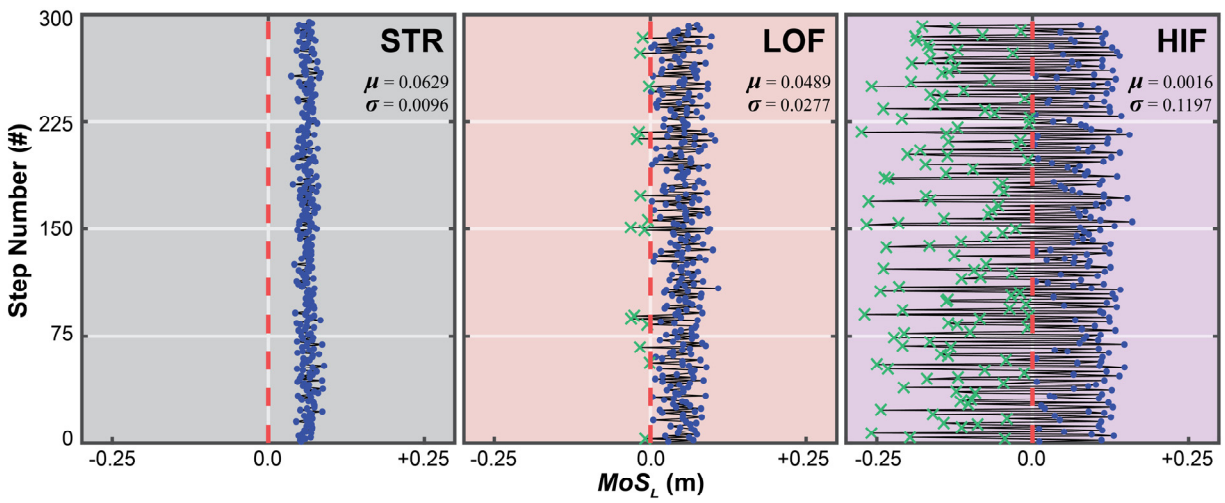


Figure 4. Example minimum lateral Margin of Stability (MoS_{Lmin}) time series (300 consecutive steps each) for three representative trials from a typical participant walking on a Wide path for each path oscillation frequency: STR, LOF, and HIF. The vertical red dashed line indicates $MoS_{Lmin} = 0$. Solid blue markers (●) indicate steps where $MoS_{Lmin} > 0$, which were considered stable. Green markers (×) indicate steps where $MoS_{Lmin} < 0$, which were considered unstable. The within-trial means (μ) and standard deviations (σ) of each MoS_{Lmin} time series are shown on each corresponding subplot.

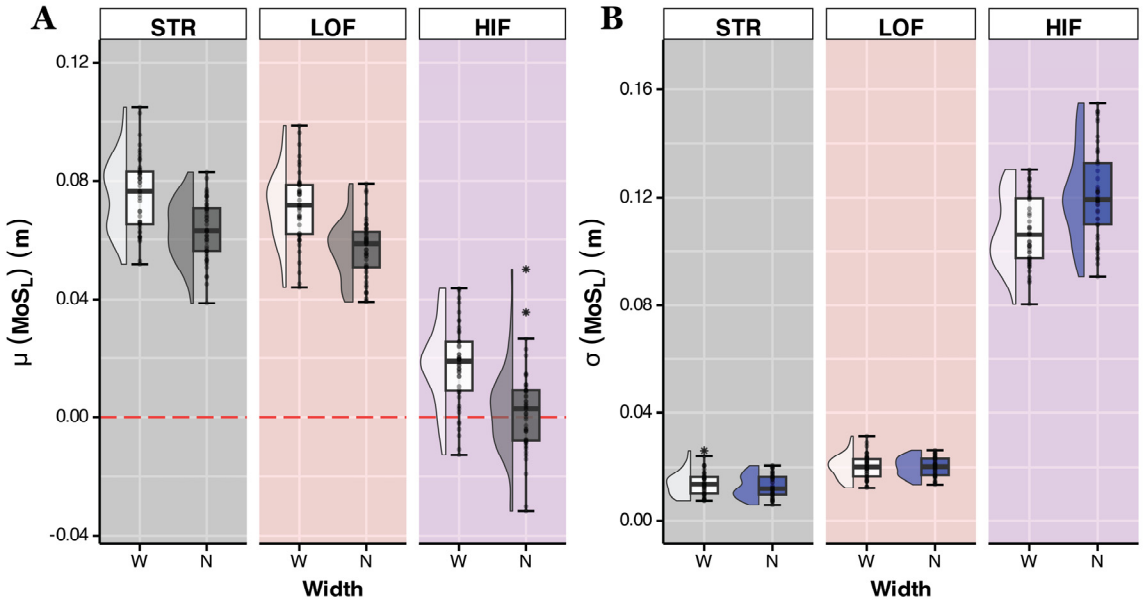
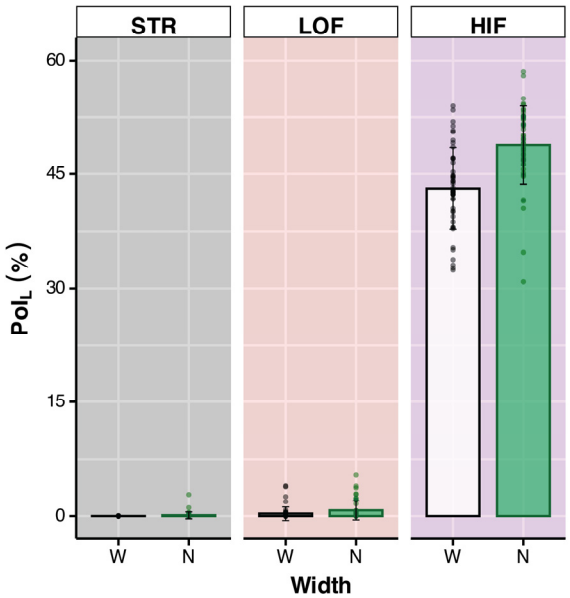


Figure 5. (A) Within-trial means (μ) of minimum lateral Margin of Stability (MoS_{Lmin}) on the wide (W) and narrow (N) paths for each path oscillation frequency: STR (grey), LOF (red), and HIF (purple). **(B)** Corresponding within-trial step-to-step standard deviations (σ) of MoS_{Lmin} for each path combination. Box plots show the medians, 1st and 3rd quartiles, and whiskers extending to 1.5 × interquartile range. Values beyond this range are shown as individual asterisks. The overlaid markers are individual data points for each participant from two separate trials**.** Half-violin plots are also shown for visual reference. The red horizontal dashed line in (**A**) indicates $MoS_{Lmin} = 0$. Results of statistical analyses are detailed in Table 2.

Figure 6. Lateral Probability of Instability (PoI_L) on the wide (W) and narrow (N) paths for each path oscillation frequency: STR (grey), LOF (red), and HIF (purple). Bar plots represent the mean values. The overlaid markers are individual data points for each participant from two separate trials. Results of statistical analyses are detailed in Table 2.



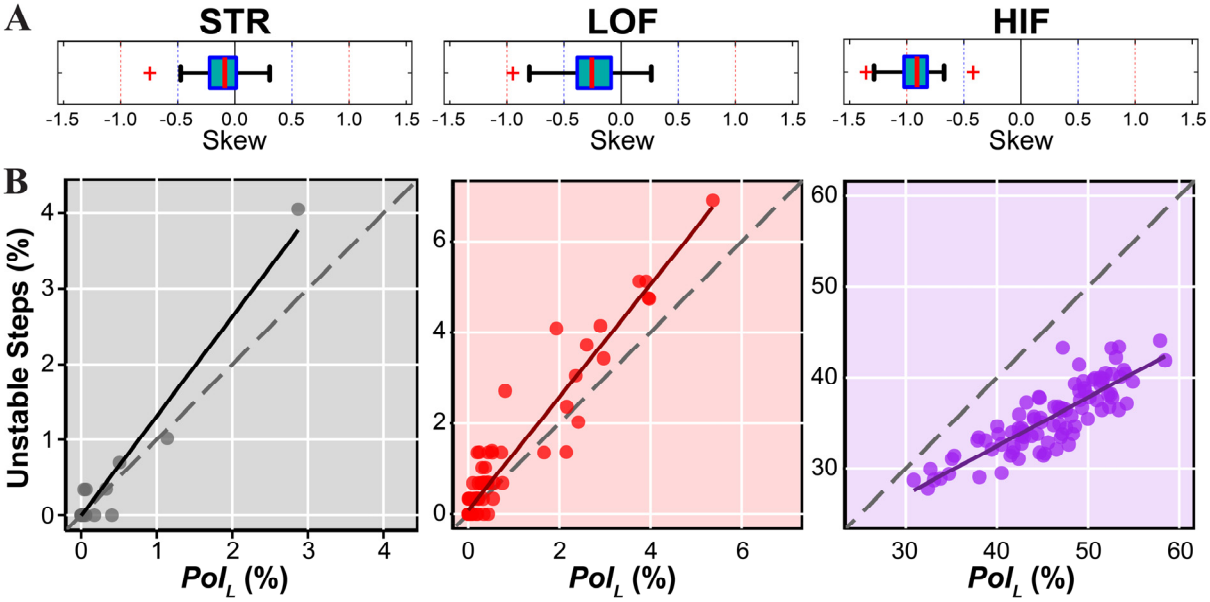


Figure 7. A) Boxplots of skewness values computed from MoS_{Lmin} time series (e.g., Fig. 5) computed from all trials pooled across both path Widths for each of the STR, LOF, and HIF path oscillation frequency conditions. Step-to-step MoS_{Lmin} distributions were predominantly symmetrical ($-0.5 <$ skewness $< +0.5$) for STR and LOF trials, but mostly moderately negatively skewed ($-1.0 <$ skewness < -0.5) for HIF. **B)** Correlations of PoI_L to direct measurements of percent unstable steps taken for each path oscillation frequency. The diagonal grey dashed line indicates the identity line. PoI_L predicts % Unstable Steps very well for STR and LOF paths, but over-estimates % Unstable Steps for HIF.