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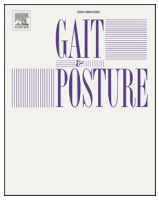

Motor adaptation of gait to bilaterally added lower-limb mass in young adults

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ABSTRACT

Background: Walking with bilaterally added lower-limb mass is a promising approach to improve gait function, but it alters the mechanics of the lower limbs. Consequently, the central nervous system needs to adapt and presumably form an internal model of the altered condition. However, this motor adaptation and de-adaptation process may jeopardize safe walking. This study aimed to analyze motor adaptation and de-adaptation in response to bilaterally added lower-limb mass.

Methods: Sixteen healthy female and male participants walked on a treadmill with and without weight cuffs attached to their thighs and shanks while full-body kinematics were recorded. Motor adaptation and de-adaptation were analyzed using discrete spatiotemporal (e.g., stride length, cadence, joint range of motion), local hip and trunk (maximum Lyapunov exponent), and global stability metrics (detrended fluctuation analysis of stride time).

Results: Only minimum toe clearance showed a motor adaptation pattern, i.e., differed at the beginning of the adaptation and de-adaptation phases (both 0.023 ± 0.006% leg length) compared to baseline (0.016 ± 0.006% leg length; $p < 0.001$), and then converged close to baseline over multiple strides. Local hip stability was reduced during adaptation (baseline: 1.43 ± 0.42, adaptation: 1.64 ± 0.61; $p = 0.017$), while local trunk (baseline: 1.57 ± 0.45, adaptation: 1.69 ± 0.56; $p = 0.301$) and global stability did not differ from baseline (baseline: 0.74 ± 0.12, adaptation: 0.71 ± 0.12; $p = 0.278$).

Significance: The results are consistent with the idea that the central nervous system rapidly selects an established walking pattern that accommodates bilaterally added lower-limb mass, suggesting a potential prioritization of safe walking.

1. Introduction

Walking provides independence and facilitates many activities of daily living [1]. However, aging and various pathologies can lead to gait deficits, resulting in immobility and loss of independence [2]. One key determinant of gait deficits is lower-limb muscle weakness [3]. Accordingly, training with added lower-limb mass has been shown to be effective for improving gait function [2,4]. This can be achieved by wearing weight vests, weight cuffs, or elastic leg bands, or by attaching braces or robotic devices [4,5]. However, adding lower-limb mass alters their mechanical properties, e.g., the moments of inertia increase. In particular, distally added mass increases the demands during the swing phase and weight acceptance at foot strike [6,7]. Furthermore, research shows that walking with bilaterally added lower-limb mass to the thighs and shanks differs from regular walking with increased stride time, stance phase, and step width [6–8]. Moreover, while changes in lower-limb angles have been found to be subtle and inconsistent [6–10], studies report that adding lower-limb mass reduces leg stability and may impair balance [9,10].

To account for changes in mechanical properties with added lower-limb mass, the central nervous system (CNS) must recalibrate its knowledge of the lower limbs' biomechanics [11], a process called

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motor adaptation [11,12]. In motor adaptation, the execution of a well-practiced skill is adjusted to maintain performance in response to a change in the environment or the body [13]. These changes cause task performance parameters to deviate from baseline, but over trials, they typically return close to baseline, often exponentially. When the changes are removed, "after-effects" occur, with deviations in the opposite direction [12]. After-effects suggest the CNS has acquired model knowledge of the changed conditions. [12]. Motor adaptation has been studied in planar reaching [12], split-belt walking [14], and walking with unilaterally added lower-limb mass [11], or exoskeletons [15]. However, motor adaptation research on bilaterally added lower-limb mass is scarce, though the perturbation and thus the recalibration process might differ: Split-belt walking and walking with unilaterally added lower-limb mass initially provoke asymmetric gait [11,14], an effect not expected with bilaterally added mass, and walking with exoskeletons involves additional factors, such as propulsion assistance and restricted degrees of freedom [16].

Despite its use in gait training, the adaptation phase (strides after adding lower-limb mass) and the de-adaptation phase (strides after removal) could exhibit additional instability [9,10]. If walking with added lower-limb mass aims to improve gait, it is crucial to understand how the CNS adapts and de-adapts to these changes before starting training safely. We hypothesize that (1) participants demonstrate an exponential adaptation to bilaterally added lower-limb mass and show after-effects upon removal, and (2) walking while adapting to the bilaterally added lower-limb mass exhibits less stability than walking without.

2. Material and methods

Earlier articles on this dataset describe dual-task analyses on steady-state gait [17,18] and preliminary results with a subsample on adaptation [19]. Here, original kinematic data and non-linear analyses for all participants are presented.

2.1. Participants

Sixteen healthy volunteers (nine females, seven males; age: 24.1 ± 3.4 years; height: 1.73 ± 0.09 m; mass: 65.1 ± 10.4 kg) participated after giving written informed consent. The Ethics Committee of the Karlsruhe Institute of Technology approved the study.

2.2. Apparatus and task

The participants walked on a treadmill (h/p/cosmos Saturn; Nussdorf-Traunstein, Germany) with and without 2.25 kg weight cuffs attached bilaterally to their thighs and shanks (Fig. 1). Sixteen cameras (200 Hz; Vicon, Oxford) captured full-body movements using a modified Master-Motor-Map marker setup with 56 markers [20].

2.3. Experimental design

After 6 min familiarizing by walking on the treadmill without weight cuffs [22], participants' preferred walking speeds were determined and subsequently maintained (1.14 ± 0.08 m/s; [23]).

The two blocks were counterbalanced across participants (Fig. 2). In the 3-minute pause between blocks, the weight cuffs were attached or detached.

2.4. Data analysis

The raw motion capture data were post-processed offline in Nexus (2.14.0; Vicon, Oxford), then low-pass filtered (6 Hz, 4th-order Butterworth) and segmented into strides [23] in MATLAB (R2023b; The MathWorks, Natick, USA). 2.4 ± 0.6 steps from the treadmill's acceleration phases were excluded.

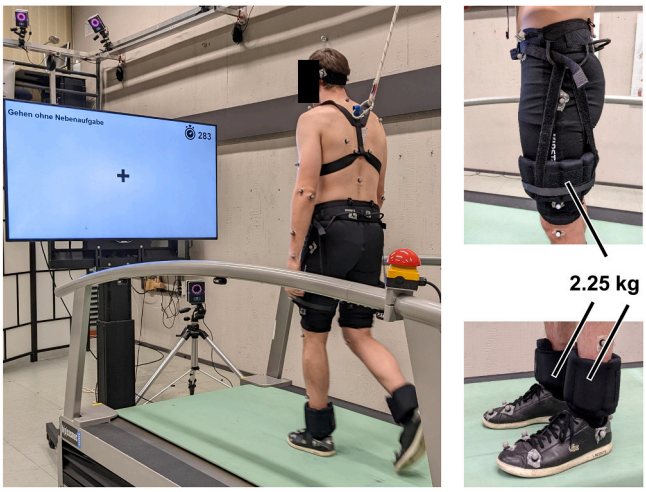

Fig. 1. Setup. An exemplary participant walks on the treadmill with weight cuffs attached. The 2.25 kg weight cuffs were attached bilaterally to the thighs and shanks. 9 kg was chosen, as it is typical for lower-limb exoskeletons [21]. A custom-made hip belt with Velcro straps ensured proper positioning of the weight cuffs, with the lower edge of the thigh weight cuff fixed 10 cm above the individual knee joint axis. A 65-inch monitor was installed 240 cm in front of the participants with its top edge at eye level. Participants were instructed to keep their eyes on the monitor displaying the dual tasks for a different part of the analysis, which is not analyzed here but elsewhere [17,18].

Since no standard parameter exists for motor adaptation to bilaterally added lower-limb mass, we chose parameters known to differ between regular walking and walking with added lower-limb mass as well as motor adaptation to unilaterally added lower-limb mass [6–8,24,25]: stride length, cadence, step width, stance phase, minimum toe clearance during the swing phase, and maximum foot clearance, normalized according to [26]. We derived the sagittal hip, knee, and ankle angles, as well as the center of mass (CoM), using OpenSim's Inverse Kinematics Tool (OpenSim v4.4) with the model by Arnold et al. [27]. Therefore, the model was scaled for each participant, with all markers given equal weight. Time normalization (100 time points) was performed using cubic spline interpolation.

Because walking with added mass has been reported to be less stable [11,12], we included non-linear parameters quantifying stability. Stability refers to the ability to sustain movement despite perturbation [28]. Attaching weight cuffs is considered a perturbation as it alters the lower limbs' inertia [29]. The local dynamic stability was quantified using the maximum Lyapunov exponent. As stationarity is required and was examined using visual inspection [28], we analyzed only hip and trunk segments, excluded thigh and shank, and focused on the vertical direction. As non-linear analysis requires at least 150 strides, we cannot compare the baseline, adaptation start, and end as in the linear analysis, but rather the complete phases. Therefore, the first 200 strides from baseline and adaptation were normalized to 200,000 points (200 strides · 100 time points; [30]). The root-sum-square of the vertical displacement of clusters of four markers attached to the respective segment yielded a 1-D time series [28,31,32]. Using this time series, a false nearest neighbor algorithm [28,33] yielded the embedding dimensions m (largest ms: $m_{hip,\ baseline} = 8$, $m_{hip,\ adaptation} = 8$, $m_{trunk,\ baseline} = 7$, $m_{trunk,\ adaptation} = 8$). Then, the time lag τ for the space reconstruction was determined using the first local minimum of the average mutual information curves (median τs: $\tau_{hip,\ baseline} = 16$, $\tau_{hip,\ adaptation} = 16$, $\tau_{trunk,\ baseline} = 16$, $\tau_{trunk,\ adaptation} = 15$). Rosenstein's algorithm was used to estimate the divergence curve [34]:

$$S(t) = [z(t), z(t+\tau), \ldots, z(t+(m-1)\tau)]$$

The slope λ of the divergence curve's short-term phase represents local stability, with a higher λ indicating lower local stability.

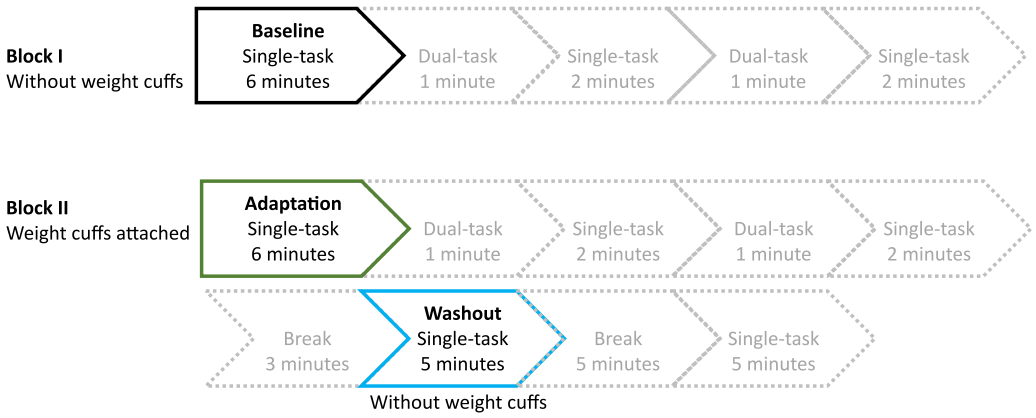

Fig. 2. Schedule. The order of blocks I and II was counterbalanced across participants. Block I was done without weight cuffs attached, and Block II with weight cuffs attached, except for the washout phase. The phases in gray are not considered further but have been analyzed in [17,18]. The preceding 6 min of treadmill familiarization are not displayed here.

Detrended Fluctuation Analysis (DFA) assessed global stability [35]. Consecutive stride time data from the same 200 strides ($w = 200$) as used for the maximum Lyapunov exponent served as the data series x, which was mean-centered and cumulatively summed, yielding profile A:

$$A(w) = \sum_{i=1}^{w} (x(i) - \bar{x})$$

Then, the profile was segmented into non-overlapping chunks of size Δn (Δn = 4–24 time points). Each chunk was fitted using linear regression (least squares). The average fluctuation (mean-squared residual) of the data series around the estimated trend F(Δn) was calculated, and this estimation was repeated for all window sizes:

$$F(\Delta n) = \sqrt{1 \Big/ N \sum_{w=1}^{N} (A(w) - A_{\Delta n}(w))^2}$$

Here, N denotes the total number of data points. If the fluctuation plot, showing F(Δn) vs. Δn on a double-logarithmic scale, is linear, the scaling exponent DFA-α, the curve's slope, quantifies the long-range correlations of the stride time data. A DFA-α between 0.5 and 1 indicates a self-similarity characteristic of the stride times, i.e., a short stride is more likely to follow a short one. Above 0.5, a higher DFA-α indicates greater data persistence, interpreted as reduced global stability [32,35].

2.5. Statistical analysis

We tested hypothesis 1 (motor adaptation and after-effects) in three steps: First, we compared the baseline (strides 115–124), start (strides 1–10), and end (strides 209–218) of adaptation. 218 was the maximum number of strides during adaptation across all participants. Normality was violated, so we used Friedman's test with the Nemenyi post-hoc procedure.

Second, motor adaptation resembles a (double-)exponential function [36]. We compared linear and exponential model fits of parameters indicating motor adaptation in the first step (MATLAB `fit`; `fittypes`: '`linearinterp`', '`exp1`', '`exp2`') using the root mean squared error (RMSE), the explained variance (R^2), and the Akaike Information Criterion (AIC). Fits were computed for each participant. Smaller RMSE and AIC and higher R^2 values indicate better fits.

Third, we assessed after-effects by comparing baseline (strides 115–124) with the first 10 washout strides using the Wilcoxon signed-rank test.

We tested hypothesis 2 (local and global stability) on the maximum Lyapunov exponents and DFA-α between the baseline (strides 1–200) and the adaptation (strides 1–200), with a Wilcoxon signed-rank test.

As the study was designed to address dual-tasking [17,18] and motor adaptation, participants either started with block I or II (see 3.3).To confirm there is no series effect in the motor adaptation analysis, we used a linear mixed model on the minimum toe clearance (MTC) data during adaptation (Matlab fitlme): MTC ~ Group * StrideNo + (StrideNo | Participant). Here, Group is a categorical variable indicating whether the participant completed block I or II first. The random slope for StrideNo allows MTC to develop participant-specifically. As neither interaction ($p = 0.97$) nor group ($p = 0.88$) was significant, group assignment did not affect motor adaptation (Supplementary Table 1).

The significance level (two-tailed) was set *a priori* at 0.05. Effect sizes were calculated as Kendall's W (Friedman test), or the r effect size (Wilcoxon signed-rank test, Friedman's post-hoc) and interpreted as small ($W \geq 0.1$; $|r| \geq 0.1$), medium ($W \geq 0.3$; $|r| \geq 0.3$), and large ($W \geq 0.5$; $|r| \geq 0.5$; [37]).

3. Results

3.1. Participants adapted to bilaterally added lower-limb mass, with typical gait parameters showing different patterns

The Friedman's tests comparing baseline, adaptation start and end was significant for all parameters, so we employed post-hoc tests to identify the key differences (Table 1) [stride length: $\chi^2(16) = 18.38$, $p < 0.001$, $W = 0.57$; cadence: $\chi^2(16) = 19.62$, $p < 0.001$, $W = 0.61$; step width: $\chi^2(16) = 16.62$, $p < 0.001$, $W = 0.52$; stance phase: $\chi^2(16) = 27.12$, $p < 0.001$, $W = 0.85$; minimum toe clearance: $\chi^2(16) = 15.50$, $p < 0.001$, $W = 0.48$; maximum foot clearance: $\chi^2(16) = 30.12$, $p < 0.001$, $W = 0.94$; vertical CoM range of motion (RoM): $\chi^2(16) = 15.50$, $p < 0.001$, $W = 0.48$; mediolateral CoM RoM: $\chi^2(16) = 24.88$, $p < 0.001$, $W = 0.78$; sagittal hip angle RoM: $\chi^2(16) = 8.38$, $p = 0.015$, $W = 0.26$; sagittal knee angle RoM: $\chi^2(16) = 26.38$, $p < 0.001$, $W = 0.82$; sagittal ankle angle RoM: $\chi^2(16) = 21.12$, $p < 0.001$, $W = 0.66$].

Minimum toe clearance and sagittal knee RoM showed a typical progression of motor adaptation (Post-hoc tests; Table 1, Fig. 3, non-normalized minimum toe clearance in Supplementary Figure 1) and were thus further investigated.

A double-exponential function resembled the minimum toe clearance progression best [linear: RMSE $= 0.004 \pm 0.001$, $R^2 = 0.21 \pm 0.21$, AIC $= -2378.16 \pm 121.32$; exponential: RMSE $= 0.004 \pm 0.001$, $R^2 = 0.21 \pm 0.21$, AIC $= -2379.75 \pm 122.68$; double-exponential: RMSE $= 0.004 \pm 0.001$, $R^2 = 0.28 \pm 0.23$, AIC $= -2397.10 \pm 128.78$; Fig. 3]. However, the linear model was the best fit for the sagittal knee angle RoM [linear: RMSE $= 1.66 \pm 0.52$, $R^2 = 0.23 \pm 0.15$, AIC $= 202.76 \pm 118.33$; exponential: RMSE $= 1.67 \pm 0.52$, $R^2 = 0.23 \pm 0.15$, AIC $= 203.08 \pm 118.39$; double-exponential:

Table 1
Parameters used to investigate motor adaptation by comparing the baseline and the adaptation phase. All percentage values are normalized to body height. Italic: The parameter resembles the progression of motor adaptation. Bold: significant values ($p < 0.05$). Abbreviations: B: baseline, S: start of adaptation, E: end of adaptation, CoM: center of mass, RoM: range of motion, f*: normalized cadence ($\sqrt{9.81/\text{leg length}}$), l_0: leg length.

	Baseline	Start Adaptation	End Adaptation	$p_{B \leftrightarrow S}$	$\lvert r_{B \leftrightarrow S}\rvert$	$p_{B \leftrightarrow E}$	$\lvert r_{B \leftrightarrow E}\rvert$	$p_{S \leftrightarrow E}$	$\lvert r_{S \leftrightarrow E}\rvert$
Stride length (% l_0)	1.53 ± 0.10	1.59 ± 0.08	1.62 ± 0.08	**0.022**	0.66	**< 0.001**	1.06	0.249	0.40
Cadence (f*)	0.51 ± 0.03	0.50 ± 0.03	0.49 ± 0.03	0.126	0.49	**< 0.001**	1.10	**0.036**	0.62
Step width (% l_0)	0.11 ± 0.04	0.14 ± 0.03	0.12 ± 0.04	**< 0.001**	1.02	0.181	0.44	0.056	0.57
Stance phase (%)	66.56 ± 0.84	64.64 ± 1.02	65.06 ± 0.77	**< 0.001**	1.28	**0.002**	0.84	0.181	0.44
Minimum toe clearance (% l_0)	*0.016 ± 0.006*	*0.023 ± 0.006*	*0.018 ± 0.006*	***< 0.001***	*0.97*	*0.333*	*0.35*	***0.036***	*0.62*
Maximum foot clearance (% l_0)	2.89 ± 0.17	2.67 ± 0.18	2.76 ± 0.16	**< 0.001**	1.37	**0.007**	0.75	**0.036**	0.62
Vertical CoM RoM (% l_0)	0.024 ± 0.004	0.025 ± 0.004	0.027 ± 0.005	0.333	0.35	**< 0.001**	0.97	**0.036**	0.62
Mediolateral CoM RoM (% l_0)	0.021 ± 0.006	0.035 ± 0.012	0.030 ± 0.011	**< 0.001**	1.24	**0.007**	0.75	0.126	0.49
Sagittal hip angle RoM (°)	43.12 ± 5.25	43.48 ± 5.35	44.91 ± 6.32	0.650	0.22	**0.013**	0.71	0.126	0.49
Sagittal knee angle RoM (°)	*62.92 ± 4.47*	*57.08 ± 4.91*	*60.60 ± 4.73*	***< 0.001***	*1.28*	*0.056*	*0.57*	***0.013***	*0.71*
Sagittal ankle angle RoM (°)	30.01 ± 6.78	25.36 ± 4.54	27.28 ± 4.98	**< 0.001**	1.15	0.056	0.57	0.056	0.57

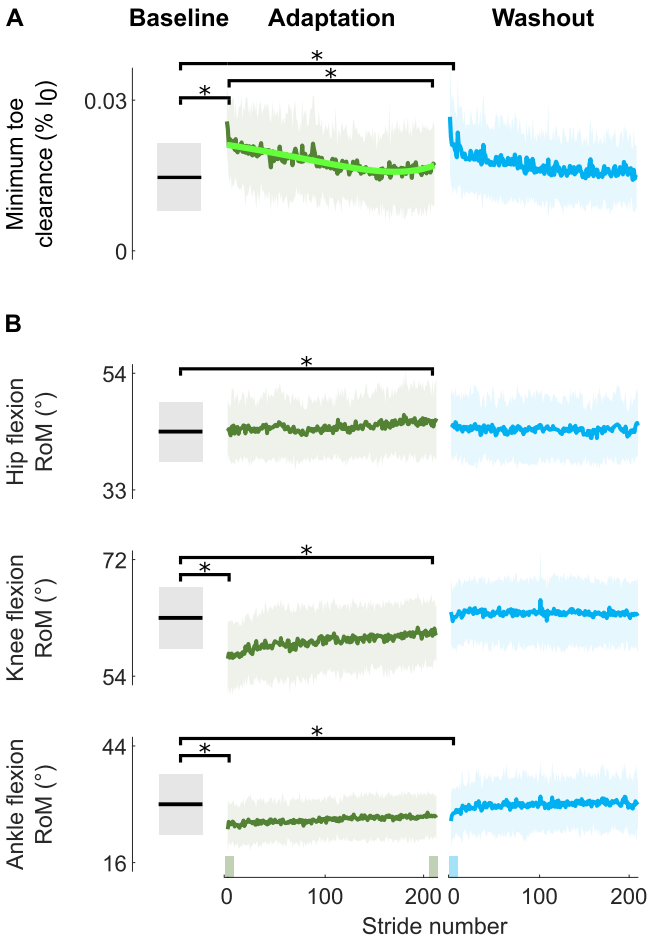

Fig. 3. Minimum toe clearance (A) and the range of motion of the sagittal hip, knee, and ankle angles (B) during baseline (black), adaptation (green), and washout (blue). The mean is shown as a solid line, and the standard deviation is shown as shaded areas around the mean. The light green line (Minimum toe clearance, adaptation) shows the double-exponential fit ($0.0270 + 0.0009 \cdot e^{0.0147 \cdot \text{stride}} - 0.0055 \cdot e^{0.0078 \cdot \text{stride}}$). The shaded horizontal areas on the x-axis indicate the range of strides used for the tests. Horizontal bars indicate significant differences ($p < 0.05$). Abbreviations: RoM: range of motion, l_0: leg length.

RMSE = 1.77 ± 0.90, $R^2 = -0.05 \pm 1.49$, AIC = 209.29 ± 170.97].

In summary, only the minimum toe clearance followed the expected motor adaptation pattern. It initially deviates from the baseline, then returns to it exponentially. The sagittal knee angle RoM initially diverges but then converges linearly. Step width, maximum foot clearance, and the RoMs of the sagittal ankle angle initially diverge, but do not fully return to baseline. Differences between baseline and adaptation are consistent, i.e., stride-invariant, for stride length, stance phase, and mediolateral CoM RoM. During adaptation, the vertical CoM RoM, cadence, and the RoM of the sagittal hip angle move away from baseline.

Furthermore, we observed after-effects for step width and stance phase (Table 2, Fig. 3). Minimum toe clearance and sagittal ankle RoM also deviated from baseline, but in the same direction as initial adaptation.

3.2. Participants walked with lower local hip stability during adaptation

The maximum Lyapunov exponent (Fig. 4) was higher during adaptation than baseline for hip [baseline: 1.43 ± 0.42, adaptation: 1.64 ± 0.61; $z = -2.379$, $p = 0.017$, $|r| = 0.59$] but did not differ for the trunk [baseline: 1.57 ± 0.45, adaptation: 1.69 ± 0.56; $z = -1.034$, $p = 0.301$, $|r| = 0.26$]. This indicates reduced local stability of the hip during the adaptation phase.

DFA-α (Fig. 4) indicated self-similarity ($0.5 < \alpha < 1$) but did not differ between baseline (0.74 ± 0.12) and adaptation (0.71 ± 0.12) [$z = 1.086$, $p = 0.278$, $|r| = 0.27$].

4. Discussion

This study analyzed motor adaptation to bilaterally added lower-limb mass. Our first hypothesis was that participants demonstrate an exponential adaptation to bilaterally added lower-limb mass and show after-effects upon removal. However, motor adaptation was found to be parameter-specific. Minimum toe clearance reflected the hypothesized pattern. This pattern has been reported previously in unilaterally added lower-limb mass and attributed to safety response mechanisms [11]. Furthermore, low minimum toe clearance is a major cause of trips and falls due to unintentional contact with obstacles or the ground [38], and studies report that minimum toe clearance initially increases after perturbations through obstacles and then decreases in subsequent strides [39]. In this context, this pattern was described as reflecting the CNS's attempt to balance perturbation avoidance with energy cost. Likewise, we propose that, for walking with bilaterally added lower-limb mass, the CNS may initially increase the minimum toe clearance to ensure safe walking before gradually reducing it to lower energy cost [40]. Contrary to our hypothesis, we found no typical after-effects in minimum toe clearance. Values were instead lower than baseline. While this contrasts with the motor adaptation literature [12,14], it has also been reported in unilaterally added lower-limb mass [11]. Accordingly, we suggest that this pattern again reflects a safety mechanism: By removing the added mass, the limbs' mechanics change, and the CNS might again prioritize safe walking.

The maximum foot clearance showed a trend toward motor

Table 2
Parameters used to investigate after-effects of motor adaptation by comparing baseline and the washout phase. All percentage values are normalized to body height. Bold: significant values ($p < 0.05$). Abbreviations: CoM: center of mass, RoM: range of motion, f*: normalized cadence ($\sqrt{9.81/\text{leg length}}$), l_0: leg length.

	Baseline	Start Washout	W	p	|r|
Stride length (% l_0)	1.53 ± 0.10	1.53 ± 0.09	85.00	0.379	0.22
Cadence (f*)	0.51 ± 0.03	0.51 ± 0.03	46.00	0.255	0.28
Step width (% l_0)	0.11 ± 0.04	0.09 ± 0.04	119.00	**0.008**	0.66
Stance phase (%)	66.56 ± 0.84	66.24 ± 1.12	107.00	**0.044**	0.50
Minimum toe clearance (% l_0)	0.016 ± 0.006	0.023 ± 0.006	0.00	**< 0.001**	0.88
Maximum foot clearance (% l_0)	2.89 ± 0.17	2.87 ± 0.17	90.00	0.255	0.28
Vertical CoM RoM (% l_0)	0.024 ± 0.004	0.023 ± 0.004	85.00	0.379	0.22
Mediolateral CoM RoM (% l_0)	0.021 ± 0.006	0.020 ± 0.006	67.00	0.959	0.01
Sagittal hip angle RoM (°)	43.12 ± 5.25	44.14 ± 5.57	40.00	0.148	0.36
Sagittal knee angle RoM (°)	62.92 ± 4.47	63.24 ± 4.50	75.00	0.717	0.09
Sagittal ankle angle RoM (°)	30.01 ± 6.78	27.91 ± 5.39	125.00	**0.003**	0.74

adaptation but did not fully return to baseline values. This is presumably a direct effect of the added mass. Facilitating the same maximum foot clearance as without added mass would have required increased moments at the lower-limb joints and, consequently, increased effort [6,7], which contrasts with the assumption that the CNS aspires for walking efficiency [40]. The RoM progressions of the sagittal knee and ankle angles tend to reflect a motor adaptation pattern, but with a linear rather than exponential convergence to baseline for the knee and incomplete convergence for the ankle. The hip sagittal RoM was hardly affected by bilaterally added lower-limb mass, as it was higher than baseline only at the end of the adaptation phase. This distal-to-proximal pattern of sagittal lower-limb joints has also been observed in studies of unilaterally added lower-limb mass and treadmill motor adaptation [22]. Perhaps this reflects the formation of an internal model, as it has been suggested that the hip muscles are more under predictive neural control than those acting on the knee and ankle [22].

Contrary to our hypothesis, stride length, stance phase, mediolateral CoM RoM, and double-support time differed consistently between baseline and adaptation, consistent with previous studies comparing steady-state walking with and without added lower-limb mass [6–8,25]. The absence of a motor adaptation pattern might indicate that participants quickly switched to an established gait pattern suited to bilaterally added lower-limb mass [14]. This may be because walking with added mass is a common task, such as when wearing hiking boots.

Regarding our second hypothesis, that walking while adapting to bilaterally added lower-limb mass exhibits less stability than walking without, we found decreased local hip stability during adaptation compared to baseline. While one might expect greater local stability during motor adaptation as a byproduct of the CNS prioritizing safety, as described earlier, our results suggest otherwise. This might be related to the ongoing recalibration process. Presumably, due to stride-by-stride adjustments, as reflected by minimum toe clearance, gait automaticity is reduced, a pattern associated with reduced stability in dual-task studies [41]. However, neither local trunk stability nor global stability differed between baseline and adaptation. We suggest that motor adaptation to bilaterally added lower-limb mass involves adjusting the lower limbs while maintaining local trunk and global stability.

Several limitations need to be addressed. As the block order was counterbalanced (see 3.3), prior conditions could have influenced motor adaptation, but additional analysis suggests they did not (see 3.5). Walking on a treadmill might limit ecological validity, but it was necessary to study motor adaptation without interruption. The sample size followed common practice in walking biomechanics but was not determined a priori by power analysis, potentially affecting precision and statistical power. Since the belt speed was fixed, participants could not adjust their walking speed as a result of motor adaptation. However, previous studies have shown that adding mass to the thigh or shank does not significantly alter walking speed [24]. Washout cannot be interpreted as a pure aftereffect due to the preceding 3-minute pause. Because we have not compared our findings with "steady-state" walking with bilaterally added lower-limb mass, we cannot rule out that the observations made from non-linear analysis are due solely to added mass. Finally, conclusions regarding safety and effort remain speculative due to the absence of direct measurements.

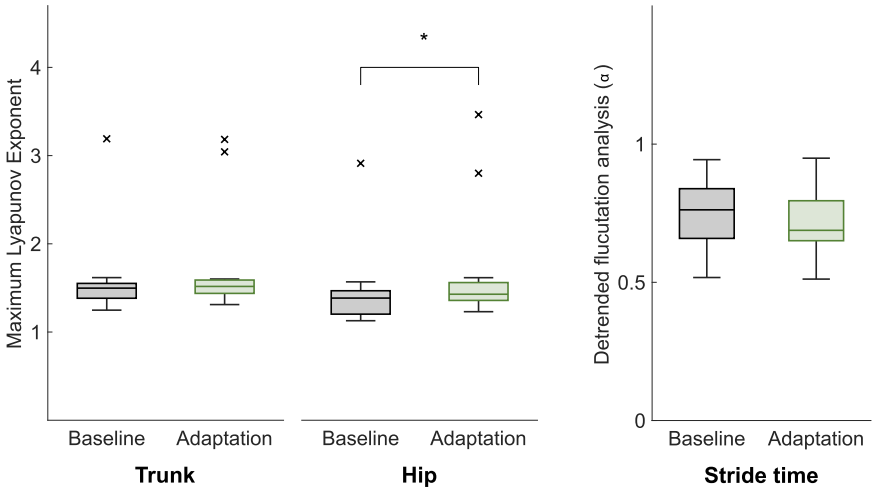

Fig. 4. Boxplots showing non-linear parameters used to investigate motor adaptation by comparing the baseline and the adaptation phase. The maximum Lyapunov exponent quantifies the local stability of the trunk and hip. DFA-α quantifies the global stability based on the stride time. Horizontal bars and asterisks indicate significant differences ($p < 0.05$).

5. Conclusion

Walking with added lower-limb mass has previously been shown to be an effective training method for improving gait function. Our findings show that although participants rapidly switched their gait pattern to accommodate the bilaterally added lower-limb mass, they might initially prioritize safe walking, as indicated by increased minimum toe clearance. Furthermore, the local hip stability was lower during adaptation. Hence, to ensure safe walking with bilaterally added mass, we propose being aware of the motor adaptation phase before progressing to training.

CRediT authorship contribution statement

Cagla Kettner: Writing – review & editing, Software. **Norman Riedel:** Writing – review & editing, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Michael Herzog:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thorsten Stein:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization. **Barbara Deml:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization. **Jonas Weber:** Writing – review & editing, Software, Investigation, Formal analysis. **Melina Beyerlein:** Writing – review & editing, Investigation.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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N/A.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gaitpost.2026.110293.

Data availability

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

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Glossary

CNS: Central Nervous System
CoM: Center Of Mass
DFA: Detrended Fluctuation Analysis
MLE: Minimum Lyapunov Exponent
RoM: Range Of Motion