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RESEARCH ARTICLE

Energy optimization during walking involves implicit processing

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ABSTRACT

Gait adaptations, in response to novel environments, devices or changes to the body, can be driven by the continuous optimization of energy expenditure. However, whether energy optimization involves implicit processing (occurring automatically and with minimal cognitive attention), explicit processing (occurring consciously with an attention-demanding strategy) or both in combination remains unclear. Here, we used a dual-task paradigm to probe the contributions of implicit and explicit processes in energy optimization during walking. To create our primary energy optimization task, we used lower-limb exoskeletons to shift people's energetically optimal step frequency to frequencies lower than normally preferred. Our secondary task, designed to draw explicit attention from the optimization task, was an auditory tone discrimination task. We found that adding this secondary task did not prevent energy optimization during walking; participants in our dual-task experiment adapted their step frequency toward the optima by an amount and at a rate similar to participants in our previous single-task experiment. We also found that performance on the tone discrimination task did not worsen when participants were adapting toward energy optima; accuracy scores and reaction times remained unchanged when the exoskeleton altered the energy optimal gaits. Survey responses suggest that dual-task participants were largely unaware of the changes they made to their gait during adaptation, whereas single-task participants were more aware of their gait changes yet did not leverage this explicit awareness to improve gait adaptation. Collectively, our results suggest that energy optimization involves implicit processing, allowing attentional resources to be directed toward other cognitive and motor objectives during walking.

KEY WORDS: Gait adaptation, Motor learning, Dual-task paradigm, Implicit and explicit cognition, Energy optimization, Exoskeletons

INTRODUCTION

Humans have a remarkable ability to adapt their gait to changing terrains, tasks and even constraints on their body. When we encounter a steep hill, navigate a crowded space or carry a heavy load, we change how we walk. Although we often do so with relative ease, the underlying control mechanism is necessarily complex. To coordinate the movements of our limbs, we adjust the time-varying activation of tens of thousands of motor units across hundreds of muscles. In turn, by altering these coordination patterns, we choose between different gaits, such as walking or running, and adapt countless gait parameters, such as speed, step frequency and limb symmetry. Our research group, and others, has recently demonstrated that gait adaptations can be driven by continuous optimization of energy expenditure – when searching the expanse of possible gaits, we often prefer and converge on those that minimize the calories we burn in a given context (Abram et al., 2019; Finley et al., 2013; Roemmich et al., 2019; Selinger et al., 2019, 2015). This is consistent with prior work, dating back decades, showing that various preferred gait parameters, such as speed, step frequency, step length and step width, coincide with energetic minimums (Bertram and Ruina, 2001; Donelan et al., 2001; Holt et al., 1995, 1991; Srinivasan and Ruina, 2006; Umberger and Martin, 2007; Zarrugh et al., 1974). However, whether energy optimization involves an 'implicit process' (occurring automatically and with minimal cognitive attention) or rather an 'explicit process' (occurring consciously with an attention-demanding strategy) remains unclear (Frensch, 1998; Kahneman, 2011; Mazzoni and Krakauer, 2006). For example, when we encounter a hill, we might implicitly slow our speed and reduce our step rate, without even realizing it (Kawamura et al., 1991; Sun et al., 1996). Or, we might see the steep terrain, judge it looks tiring, and explicitly decide on a strategy to slow down and alter our angle of approach to reduce steepness. Both implicit and explicit processes may be used to reduce energy expenditure, either in isolation or in unison.

Dual-task paradigms have been used to assess to what extent a task is implicit or explicit in nature. Typically, a 'primary task' of interest is simultaneously performed with a 'secondary task' known to require explicit processing, such as counting backwards or stating the colour of text incongruent with the word it spells (Beauchet et al., 2005; Bench et al., 1993; Kahneman, 1973; Stroop, 1935). The theory underlying this design is that our cognitive attention is a 'limited capacity resource' – we can only think and explicitly strategize about so many things at a time (Magill, 2011; Schmidt and Lee, 2011; Woollacott and Shumway-Cook, 2002). Therefore, if the secondary task is sufficiently challenging and the primary task is explicit in nature, performance on one or both tasks will be hindered. Alternatively, if the primary task is implicit in nature, performance decrements should not occur. For example, dual-task paradigms have been used to interrogate the role of explicit control in walking. In able-bodied adults, during unperturbed walking in a predictable environment, walking is primarily an implicit process (Lajoie et al., 1993; Malone and Bastian, 2010; Paul et al., 2005; Regnaux et al., 2005). Regardless of the nature of the secondary explicit task, be it counting backward, verbally repeating sentences or buttoning a shirt, walking performance characteristics, such as speed, step length and the variability of each, are largely unchanged (Beauchet et al., 2003; Ebersbach et al., 1995; Lajoie et al., 1999; Paul et al., 2005). However, this is not the case in all contexts and for all populations. Dual-task paradigms have been used to demonstrate the enhanced role of explicit control when navigating obstacles during walking or when stepping to defined visual targets like one might encounter on a stone path (Mazaheri et al., 2014; Peper et al., 2012; Sparrow et al., 2002; Weerdesteyn et al., 2003). They have also been used to demonstrate that in children, older adults and individuals with cognitive impairments, even unperturbed

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straight-line walking can involve significant explicit control, evidenced by slowing gait speeds and increased variability under the demands of a secondary task (Beauchet et al., 2003; Hagmann-von Arx et al., 2016; Lajoie et al., 1999; Lindenberger et al., 2000; Montero-Odasso et al., 2012; Theill et al., 2011). Dual-task paradigms are a tool to probe the nature of explicit control during movement and have been used extensively in walking contexts.

Although dual-task paradigms have been used for decades to probe the nature of various well-learned motor tasks such as walking, they have only recently been applied to the ‘adaptation’ of motor tasks (Conradsson et al., 2019; Malone and Bastian, 2010; Taylor et al., 2014; Taylor and Thoroughman, 2007). Motor adaptation, where a well-learned movement is modified in response to a new context through trial and error, has long been assumed to be an implicit process (Benson et al., 2011; Masters et al., 2008; Mazzoni and Krakauer, 2006; Willingham, 1998). For example, in canonical force-field paradigms, where forces from a robotic manipulandum alter limb dynamics during reaching, a common understanding is that adaptation is driven by sensory-prediction errors that update an internal model (or stored prediction) of the task dynamics (Shadmehr et al., 2010; Shadmehr and Mussa-Ivaldi, 1994). This recalibration was thought to be primarily automatic, occurring below the level of conscious control. However, subsequent work has revealed that explicit processes can play a significant role in adaptation (Conradsson et al., 2019; Malone and Bastian, 2010; Taylor et al., 2014; Taylor and Thoroughman, 2007). In one experiment, Taylor and Thoroughman (2007) had participants perform a tone discrimination task (secondary explicit task) while adapting to perturbations from a novel force-field during reaching (primary task). They found that the ability of participants to correct arm position during a given movement was not affected, but adaptation from one reach to the next was (Taylor and Thoroughman, 2007). This implies that within-movement feedback control may be primarily implicit, but that movement-to-movement error corrections and the updating of predictive control involves explicit strategy (Taylor and Thoroughman, 2007). In later visuomotor adaptation experiments, Taylor et al. (2014) confirmed these findings and were able to decouple the contribution and time course of implicit and explicit processes during adaptation by asking participants to verbalize their aiming direction (state their explicit strategy) at the onset of each reach. Evidence from walking paradigms has provided further evidence that motor adaptation can in fact involve explicit strategy. In split-belt treadmill walking paradigms, where participants adapt to belts travelling at different speeds under each foot, explicit secondary tasks can disrupt adaptation, particularly in older adults (Conradsson et al., 2019; Malone and Bastian, 2010). This disrupted adaptation is characterized by a longer rate of adaptation in the distraction group during the adaptation period, suggesting that adaptation to the split-belt paradigm is slower when distracted by a secondary task owing to increased cognitive demands. Interestingly, there are conflicting results during de-adaptation. Conradsson et al. (2019) found no difference in de-adaptation rate between control and dual-task groups. In contrast, Malone and Bastian (2010) found that participants in the dual-task group exhibited longer de-adaptation rates, indicating better retention of the adapted gait pattern. Overall, the current understanding is that motor adaptation, whether in discrete upper-arm reaching tasks or continuous lower-limb walking tasks, can involve both implicit and explicit processes.

Verbalization of perceived effort has recently been used to probe the explicit nature of adaptation toward energy optima during walking. Reber (1989) originally described an implicit experience as being able ‘to “get the point” without really being able to verbalize what it is that one has gotten’. In other words, if you cannot verbalize your strategy, it is likely implicit. By a similar logic, if you cannot verbalize what gaits are more or less energetically demanding, you are unlikely to be performing explicit energy optimization. To probe this, Sánchez et al. (2017) asked participants to rate their perceived exertion (Borg, 1982) during split-belt walking. Despite finding that energetic cost decreased as participants adapted toward symmetry, they found no correlation between perceived exertion ratings and either metric, suggesting that adaptation may be implicit (Sánchez et al., 2017). Another group, focused on adaptations to reduce energy expenditure during exoskeleton walking, recently tried to quantify the ‘just noticeable difference’ for metabolic energy expenditure (Medrano et al., 2020). They estimated it to be roughly 25%, which is well above cost savings achieved for nearly all state-of-the-art exoskeletons (Sawicki et al., 2020), further suggesting implicit energy optimization in walking. However, these data were derived from a single participant and, intuitively, the 25% is likely an overestimate. For example, this would be equivalent to being unable to detect the energetic cost of carrying weights less than roughly 15 kg (Browning et al., 2007). Both of these recent studies by Sánchez et al. (2017) and Medrano et al. (2020) suggest energy optimization may be an implicit process, but neither directly test this question by experimentally interfering with explicit cognitive processes.

Here, we use a dual-task paradigm to probe the contributions of implicit and explicit processes in energy optimization during walking. We define energy optimization, our primary task of interest, as the process of adapting one’s gait to minimize metabolic energy expenditure. To study the energy optimization process, we leverage our previous experimental paradigm where robotic exoskeletons were used to shift people’s energetically optimal step frequency to frequencies lower than normally preferred (Selinger et al., 2019, 2015). We evaluate performance in this task by adaptation toward the energy optima, measured by decreases in step frequency. We have previously shown that people adapt to energy optimal step frequencies when performing only this task (in a single-task context). Here, we add a secondary tone discrimination task to this primary energy optimization task. This explicit secondary task requires that participants indicate whether a current audio tone is of higher or lower frequency than the previous tone. Performance in this task is evaluated in terms of accuracy (correct responses) and reaction time (time to respond). One hypothesis is that energy optimization during walking involves implicit processing and performance in both tasks will be maintained. This would be consistent with the more traditional perspective that the control of well-learned movements and the motor adaptation of these movements are largely automatic and occur below the level of conscious control (Lajoie et al., 1993; Malone and Bastian, 2010; Medrano et al., 2020; Paul et al., 2005; Regnaux et al., 2005; Sánchez et al., 2017; Shadmehr et al., 2010). This would allow for attentional resources to be directed toward other movement objectives and more complex optima to be implicitly discovered over sufficient time scales. An alternative hypothesis is that energy optimization involves explicit processing and performance on one or both tasks will deteriorate. This would be consistent with the more recent findings that motor adaptation, in both reaching and walking paradigms, can result from conscious execution of an explicit strategy (Conradsson et al., 2019; Malone and Bastian, 2010; Taylor and Thoroughman, 2007). This would suggest that attentional resources should be preserved for the energy optimization process during locomotor rehabilitation or assistive device habituation, and that explicit coaching toward the optima may be an effective strategy.

MATERIALS AND METHODS

Participants

We performed testing on a total of 11 healthy adults (7 female, 4 male) with no known gait, cardiopulmonary or cognitive impairments. Simon Fraser University's Office of Research Ethics approved the protocol, and participants gave their written, informed consent before testing. In addition, a subset of 14 participants from our previous single-task experiment were analyzed for comparison (Selinger et al., 2019).

Primary energy optimization task

To create a task in which participants had to adapt their gait in order to minimize energy expenditure, we leveraged our previous paradigm where robotic exoskeletons are used to shift people's energetically optimal step frequency. We have previously shown, in a single-task context, that people adapt toward energy optimal step frequencies (Selinger et al., 2019, 2015). We used custom software to measure and control the magnitude of the resistive torque applied to the knees in real time at 200 Hz (Simulink Real-Time Workshop, MathWorks) (Fig. 1A). In our current experiment, all participants experienced a 'penalize-high' control function where the resistive torque, and therefore added energetic penalty, was minimal at low step frequencies and increased as step frequency increased (Fig. 1B) (Selinger et al., 2015). This function reshapes the energy landscape – in this case the relationship between step frequency and energetic cost – creating a positively sloped energetic gradient at the participants' naturally preferred step frequency, and an energetic minimum at a lower step frequency (Fig. 1C). To implement this control function, we made the commanded resistive torque to the exoskeleton proportional to the participants' step frequency measured from the previous step. To measure step frequency at each step, we calculated the inverse of the time between foot contact events, identified from the fore–aft translation in ground reaction force centre of pressure from the instrumented treadmill (FIT, Bertec Inc.). We sampled ground reaction forces at 200 Hz (NI DAQ PC1-6071E, National Instruments Corporation). When commanding step frequency to the participants, we used a custom auditory metronome (Simulink Real-Time Workshop, MathWorks). Full details about the exoskeleton hardware, controller and paradigm can be found in our previous papers (Selinger et al., 2015, 2019). To keep all aspects of our instrumentation the same as in our single-task experiment (Selinger et al., 2019), we also instrumented participants with the indirect calorimetry equipment (VMax Encore Metabolic Cart, VIASYS®).

Secondary tone discrimination task

To create a secondary explicit task, we used a 'one-back' audio tone discrimination task (Fig. 1D). In this task, participants listened to a stream of auditory tones and continually distinguished whether the present tone was of higher or lower frequency than the tone immediately preceding it (one-back) (Kane et al., 2007). In pilot testing (n=2), under natural walking conditions (no exoskeleton), we also explored a simpler 'paired-tone' task, where participants distinguished the frequency between two tones presented sequentially and can then discard them from memory (Taylor and Thoroughman, 2007), as well as a more complex 'two-back' task, where the participants must continually distinguish whether the present tone is of higher or lower frequency than the second from last tone preceding it (two-back) (Kane et al., 2007). Consistent with findings from Taylor and Thoroughman (2007), we found that the paired-tone task may not be challenging enough to sufficiently tax the explicit cognitive process. Average scores were consistently above 90%. Conversely, we found the two-back task was likely too challenging (correct response rates only slightly higher than 50% chance rate), risking participant disengagement. We settled on the one-back task, for which average responses were just above 80% in piloting.

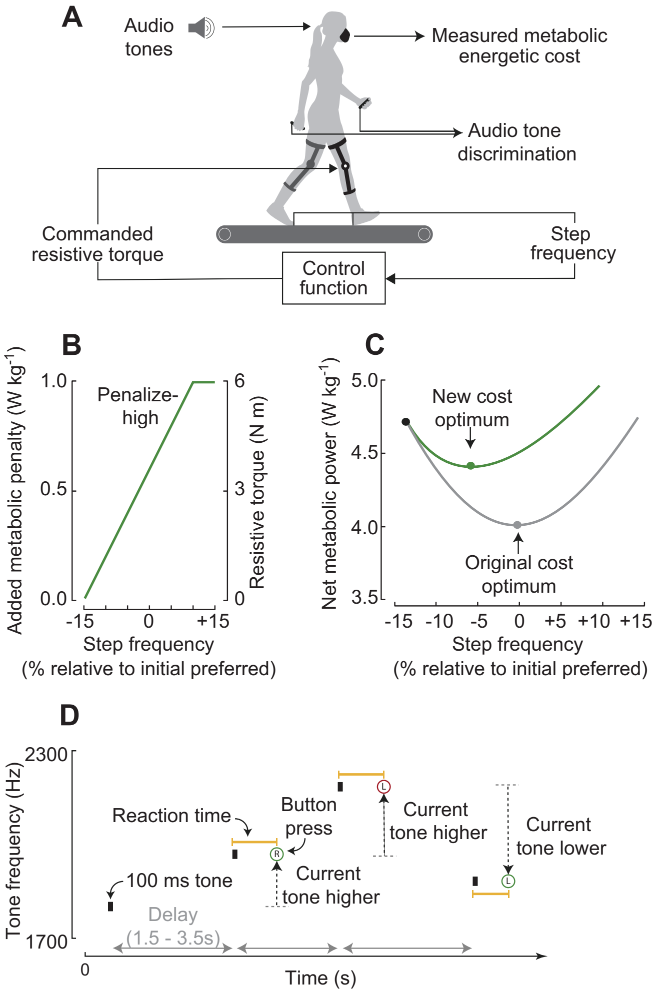

Fig. 1. Dual-task experimental design. (A) To create the primary energy optimization task, a control function commands resistive torques to the knee exoskeletons that are proportional to step frequency, making higher step frequencies energetically costly and lower step frequencies less costly. To create the secondary tone discrimination task, audio tones are presented, and the participant must indicate if the frequency of the current tone is higher or lower than the preceding tone by pressing a button held in the right or left hand, respectively. (B) Design of the penalize-high control function. (C) Schematic energetic cost landscape of the penalize-high control function (green) and the original cost landscape (grey). (D) In the secondary task, we used custom software to output a steady stream of 100 ms audio tones (black rectangles) with a frequency between 1700 and 2300 Hz. The time between tones randomly varied from 1.50 to 3.50 s (horizontal grey arrows). Left-hand and right-hand button presses are represented by circles encompassing a L or R, respectively. A button press circle coloured green indicates a correct response, while red indicates an incorrect response. The dashed vertical arrows indicate the difference in frequency between the current tone and the preceding tone. Reaction times, from onset of tone to button press, are indicated by the horizontal yellow lines.

To implement the one-back tone discrimination task, we output the stream of audio tones to a speaker using custom software (MATLAB 2013b, MathWorks) (Fig. 1D). We made the duration of each tone 100 ms, while the time between tones ranged from 1.50 to 3.50 s, chosen randomly from a uniform distribution (Taylor and

Thoroughman, 2007). To output tones of continuously varying frequencies, we created a three-tone loop. The frequency of the first tone in the three-tone loop was randomly selected from a uniform distribution (2000±150 Hz). The second and third tones in the three-tone loop occurred at a frequency ±150 Hz of the first tone, chosen randomly from a uniform distribution. The participants held a thumb activated push-button in each hand and we gave them the following instructions: 'You will be conducting a one-back audio discrimination task over the duration of each trial. That means you will listen to a stream of tones and compare the tone you just heard to that immediately before it. You are comparing tones in terms of higher or lower sound. Once you have determined that the tone you just heard was higher or lower than that immediately preceding, indicate your response via a button press. A left button press means lower and a right button press means higher. Just remember, left equals lower.'

We collected button press analog signals, as well as tone frequency, timing and duration, through a data acquisition board (BNC-2110, National Instruments) using a custom software script (MATLAB 2013b, MathWorks). To ensure that participants understood the instructions and could adequately execute the secondary task, they practised during a 1-min sample of the tone discrimination task, prior to our experimental protocol, while standing.

Experimental protocol

We replicated the protocol of our previous experiment (Selinger et al., 2019), but with the addition of the secondary tone discrimination task. This was done to allow us to directly compare dual-task and single-task results. Replicating the protocol from the single-task experiment allows us to attribute changes in performance in the primary energy optimization task to the addition of the secondary tone discrimination task. The protocol consisted of four testing periods: Baseline Period, Habituation Period, First Experience Period and Second Experience Period (Fig. 2). Participants performed the secondary tone discrimination task throughout the entirety of all four periods while walking on the treadmill at 1.25 m s^{-1}. We provided 5–10 min of rest between each period. During the Baseline Period, participants walked for 12 min with the exoskeleton controller turned off (Fig. 2A). We used this period to determine participants' 'initial preferred step frequency' under natural conditions, calculated as the average step frequency during the last 150 s of the period. During the Habituation Period, to familiarize participants with walking at a range of step frequencies while completing the tone discrimination task, we instructed participants to match their steps to both high and low frequency metronome tempos (+10% and −15% of their initial preferred step frequency, respectively) over the course of 18 min (Fig. 2B). The controller remained off during this period. During the First Experience Period, after 6 min the exoskeleton controller was turned on for the first time and participants walked for an additional 12 min while experiencing the new cost landscape (Fig. 2C). We used this period to determine whether participants were 'spontaneous initiators' (individuals that adapt toward the optima prior to any perturbation toward higher or lower cost gaits; see 'Identifying spontaneous initiators' below). In our prior single-task experiment, we found this to be a small subset of participants (6 of 36) (Selinger et al., 2019). We calculated the 'first experience preferred step frequency' as the average step frequency during the final 150 s of this period. During the Second Experience Period, participants continued to be exposed to the new cost landscape while being held at higher and lower cost gaits (higher and lower step frequencies) by a metronome (Fig. 2D). In our prior single-task experiment, we found this was necessary to initiate optimization in most non-spontaneously initiating participants (Selinger et al., 2019). The metronome tempos were again set to −15% and +10% of initial preferred step frequency to allow participants to experience the extremes of the new cost landscape, while avoiding step frequencies directly to the optima or initial preferred step frequency (approximately −5% and 0% of initial preferred step frequency, respectively). We played each high and low metronome tempo for 3 min, four times each in alternating order, with the first tempo direction randomized. Following each metronome tempo, the metronome turned off for 1-min probes of participants' self-selected step frequency. We informed participants that at times the metronome would be turned on, during which they should match their steps to the steady-state tempo, and that when the metronome turned off, they no longer had to remain at that tempo. We did not give participants any further directives about how to walk. During the final 3 min of this period, the exoskeleton controller turned off, returning participants to their natural energetic landscape. We calculated the 'final preferred step frequency' as the average step frequency during the 150 s of the period just prior to the exoskeleton controller turning off. To assess participants' de-adaptation when

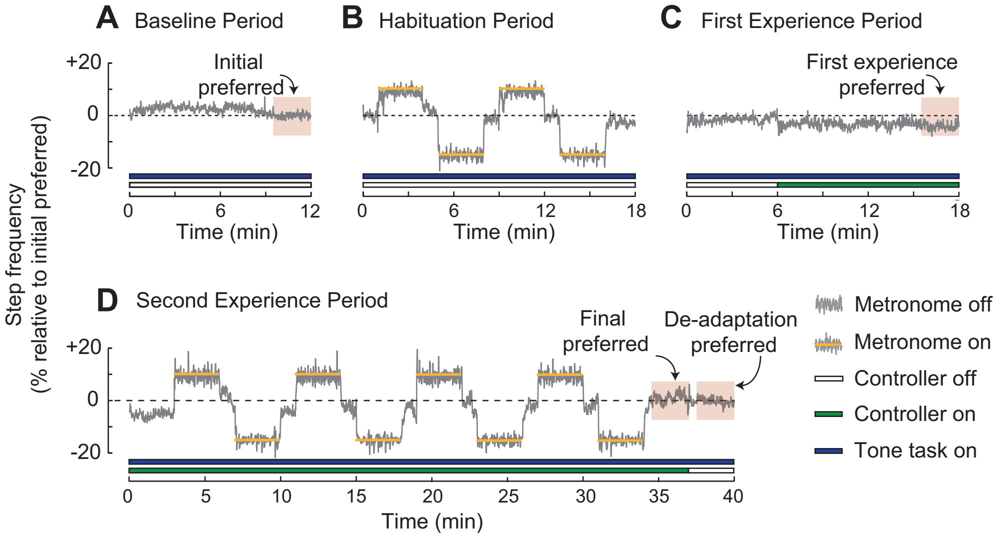

Fig. 2. Experimental protocol. Each participant completed four periods: (A) Baseline Period, (B) Habituation Period, (C) First Experience Period and (D) Second Experience Period. We provided participants with 5–10 min of rest between each testing period. Data shown are from one representative participant. Light red shaded regions indicate time periods over which we averaged step frequency data to determine our primary outcome measures.

returned to the natural cost landscape, we calculated the ‘de-adaptation preferred step frequency’ as the average of the final 150 s of the Second Experience Period, after the exoskeleton controller turned off. To determine whether participants could articulate an explicit strategy for this energy optimization process, we administered a survey following the final collection period. We asked participants to answer five free-form questions (Table 1) in an online platform (Google Forms). We designed these questions to probe their level of awareness and perception of control during optimization.

Our dual-task protocol described above does deviate from the previous single-task protocol in a few ways. First, the original single-task experiment used four different metronome tempos (−15%, −10%, +5% and +10%), while here we used only the two extremes (−15% and +10%). We did so because in our prior experiment we found different effects of probe direction (i.e. +10% versus −10%), but not magnitudes (i.e. −10% versus −15%). Here and in other studies subsequent to the single-task experiment (Abram et al., 2019; Selinger et al., 2019; Simha et al., 2019, 2021), we have chosen to simplify our protocol to a single high and low tempo, which are used during both the Habituation Period and the Second Experience Period. Second, in the original single-task experiment, the Second Experience Period was 30 min in length, while here it is 40 min owing to the addition of two extra metronome bouts. This change to a longer Second Experience Period was made to allow us to further investigate the time course of adaptation. However, we have subsequently found that adaptation following metronome holds is largely complete after 20 min and so do not expect the protocol change to have a significant effect (Abram et al., 2019). Third, in the original single-task experiment, the exoskeleton controller remained on for 6 min following the last metronome hold, while here in our dual-task experiment it remained on for only 3 min. We made this protocol change to help reduce the total length of the period for participants and because in the original single-task experiment we found adaptation during the final probe to be rapid and complete within tens of seconds (time constant: 10.5±1.8 s) (Selinger et al., 2019). When calculating final preferred step frequency in this dual-task experiment, we therefore used a 150-s window of time starting 30 s after the final metronome hold, whereas in the original single-task experiment we used a 180-s window of time starting 180 s after the final metronome hold. To ensure our primary outcome measure was not affected by this difference, we recalculated the final preferred step frequency from the original single-task experiment data set using the earlier and shorter time window that we use here.

Table 1. Survey questionnaire: participants in the single-task and dual-task experiments answered these five questions in an online form following the final collection period

Question	Keywords*	Question
1	Changed your gait?	When you were walking naturally (no metronome), did you change how you walked? If so, in what way and why?
2	Made conscious decisions?	When you were walking naturally (no metronome), were you making conscious decisions to change how you walked? If so, how did you make these decisions? And, when did you start making these decisions?
3	Had control over exo?	Did you feel that you had any control over what the exoskeleton was doing? If so, in what way?
4	How exo worked?	How was the exoskeleton making walking easier or harder?
5	Exo walking characteristic?	Did you think any walking characteristic was related to what the exoskeleton was doing? If so, state what characteristic and explain how you thought it related to what the exoskeleton was doing.

*Keywords were not provided to participants or response raters but are included here and used in Fig. 5 to allow for easier interpretation.

Experimental outcome measures

To assess performance on our primary energy optimization task, we tested whether participants adapted toward the energy optima. To do so, we tested whether the average final preferred step frequency decreased from the initial preferred step frequency using a one-sample one-tailed *t*-test and a significance level of 0.05. To test whether adaptation toward energy optima was affected by the secondary tone discrimination task, we compared the average final preferred step frequency from our dual-task experiment with that from the previous single-task experiment, calculated over the same time window. We did so using a two-sample two-tailed *t*-test with a significance level of 0.05. To determine our minimum required participant number, we performed an *a priori* power analysis for our primary outcome measure – step frequency adaptation. Based on our two previous studies (Selinger et al., 2019, 2015), we expected complete energy optimization to result in participants decreasing their step frequency by approximately 5% and with an across-participant standard deviation of approximately 3.5%, when exposed to the penalize-high controller. To detect an across-participant average difference in step frequency of at least 5%, given an across-participant average standard deviation in step frequency of 3.5% and a single-task participant number of 14, we calculated that we required a minimum of only four dual-task participants to achieve a power of 0.8. Unfortunately, to detect smaller differences in step frequency, a prohibitive number of participants would be required. For example, detecting 2.5% or 1% differences would require nearly 100 and over 10,000 participants, respectively. Therefore, in our experiment we chose to test 11 participants, increasing our expected power to over 0.9 when detecting complete versus fully abolished step frequency adaptation. However, it is important to note that we are only able to test whether the addition of a secondary explicit task fully prevents energy optimization.

We also tested whether the adaptation rate was affected by the secondary tone discrimination task. Because most of our participants were non-spontaneous initiators, who required a metronome hold at a low-cost gait before initiating adaptation, we compared the adaptation rate following the first low hold. We defined the adaptation rate as the time to reach steady-state step frequency during the 1-min release period. For each participant, we first calculated the average and standard deviation in step frequency during the final 20 s of the release period. We then defined the steady-state frequency as being within this average ±1 standard deviation. Next, we identified the first time point when the step frequency fell within this steady-state region for at least 2.5 s (roughly equivalent to five consecutive steps). We term this time the adaptation rate. To test for differences in adaptation rates between the dual-task and single-task participants, we used a two-sample, two-tailed *t*-test with a significance level of 0.05. If energy optimization is entirely implicit, we would expect similar adaptation rates between single- and dual-task participants (because the distraction task should only disrupt explicit processes and should therefore have no effect). If energy optimization requires explicit processing, we would expect faster rates of adaptation in the single-task experiment (because in the absence of distraction, participants could use attentional resources to explicitly process the demands of the task) (Malone and Bastian, 2010; Roemmich et al., 2016). For plotting purposes only, we averaged and normalized step frequency data across participants. To normalize, we first used the 1-min steady-state portion of data before metronome release to obtain a baseline steady-state value, which we subtracted from the step frequency data. Then, we divided the data by the amplitude of the change in step frequency, determined by the average of the steady-state period after release (final 20 s of release). This allows us to normalize step frequency data between 0 and 1, allowing for easier visual comparison of rates.

To assess participants' de-adaptation when returned to the natural cost landscape, we tested whether participants returned to their initial preferred step frequency and the rate at which they converged back to their initial preferred step frequency when the exoskeleton was turned off. To determine whether de-adaptation preferred step frequency values were different from initial preferred step frequency values (0%), we used a one-sample two-tailed *t*-test with a significance level of 0.05. To assess the de-adaptation rate, we calculated the time to reach steady-state for each participant, from 1 min immediately following the moment when the exoskeleton turned off (minutes 37–38 of the Second Experience Period) using the same approach describe above for adaptation.

To assess performance on the secondary tone discrimination task, we calculated response accuracies and reaction times. We calculated these metrics for the same 150-s time windows over which we calculated the initial preferred step frequency during the Baseline Period and the final preferred step frequency during the Second Experience Period. We calculated response accuracy as the percentage of correct button presses during a given time window. We calculated reaction time as the time between presentation of a tone and the onset of a button press, determined by a threshold. To confirm that the secondary tone discrimination task was challenging and required an explicit strategy, we compared participants' reaction times during the Baseline Period with an average reaction time from a previous experiment where participants completed a simple button press task (Stuss et al., 1989). We had no reason to believe that reaction time in the tone discrimination task would be faster than reaction time in a simple button press task because of the added cognitive demands of the tone discrimination task. Therefore, we used a one-sample one-tailed *t*-test with a significance level of 0.05. To determine whether performance on the secondary tone discrimination task was affected by the primary energy optimization task, we compared reaction times and accuracy scores during the Baseline Period (when the exoskeleton was off and the energy optima was unchanged) with those during the Second Experience Period (when the exoskeleton was on and the energy optima had shifted to a lower step frequency). We did so using paired-sample two-tailed *t*-tests with a significance level of 0.05. To determine whether the metronome had an effect on the secondary tone discrimination task, we compared accuracy scores in the tone discrimination task when the metronome was on and off. For each participant, we averaged accuracy scores for all time points when the metronome was on and all time points when the metronome was off during the Habituation Period (Fig. 2B). To test for differences in performance when the metronome was on and off, we used a paired-sample two-tailed *t*-test with a significance level of 0.05.

To assess participants' ability to articulate a strategy for the energy optimization process, we compared survey responses from participants in our dual-task experiment with those from the single-task experiment using three independent and blinded raters. If participants cannot articulate how they converged on lower cost gaits, this suggests the presence of an implicit learning process (Reber, 1989). All participant responses for a given question, from both the single-task and dual-task experiments, were randomized. Each of the three raters then independently rated all responses for one question (starting with question 1) before moving on to the next. We did not tell raters if the response was from a participant in the single-task experiment or our dual-task experiment. We asked raters to score each response in terms of participant 'awareness' and 'control' using a 0 to 6 scale. We gave raters the following definitions. 'Awareness' refers to the participant's awareness of the relationship between stride length/step frequency and resistance from the exoskeleton. A rating of 0 means the participant is unaware of the relationship and a rating of 6 means the participant is fully aware. 'Control' refers to the participant's reporting that they changed their stride length/step frequency to control the exoskeleton. A rating of 0 means the participant did not consciously change their gait and a rating of 6 means they did consciously change their gait.' Raters fully understood our energy optimization paradigm, the exoskeleton control function and the experimental hypotheses. To compare awareness and control scores between single-task and dual-task participants, we averaged scores across raters to obtain a single score for each participant on each question. We had no reason to believe that scores for the dual-task participants would be higher than scores for the single-task participants because we expect them to have less available attentional resources. Therefore, we used a two-sample one-tailed *t*-test with a significance level of 0.05 to test for differences for each of the five survey questions. For all statistical tests performed in our study, we had *a priori* hypotheses and therefore did not perform corrections for multiple comparisons (Perneger, 1998; Rothman, 1990).

Identifying spontaneous initiators

Some participants spontaneously initiated energy optimization, during the First Experience Period, prior to any perturbation to lower or higher cost gaits. To keep our analysis consistent with that from our previous single-task experiment, we tested for the presence of these spontaneous initiators during the First Experience Period and excluded them from all further analyses (Selinger et al., 2019). To identify spontaneous initiators, we used the same two criteria as previously reported. First, the average step frequency at the end of the First Experience Period, the first experience preferred step frequency, must be below three standard deviations in steady-state variability, determined from the time window used to calculate initial preferred step frequency. Second, the change in step frequency cannot be an immediate and sustained response to the exoskeleton turning on. To ensure that this was true, first experience preferred step frequency had to be significantly lower than the average step frequency measured from seconds 10 to 40 after the exoskeleton turned on. We expected first experience preferred step frequency to be lower than average step frequency measured from seconds 10 to 40 after the exoskeleton turned on because this would indicate participants' spontaneous adaptation toward energetic optima. Therefore, we used a two-sample one-tailed *t*-test with a significance level of 0.05. We also tested whether there was a difference in the proportion of participants identified as spontaneous initiators between our dual-task experiment and the previous single-task experiment. To do so, we used a binomial distribution model with a cumulative distribution function to calculate the probability of identifying at least as many spontaneous initiators as we did in our dual-task experiment, given the prior proportion of spontaneous initiators in the single-task experiment.

RESULTS

Identifying spontaneous initiators

We identified three of the 11 participants to be spontaneous initiators. Although this proportion (3/11, 27%) is higher than that reported in our previous single-task experiment (6/36, 17%), it is not significant (we estimate a 28% chance of finding at least this many spontaneous initiators). However, our small sample sizes only allow us to detect a difference in proportion of spontaneous initiators of roughly 2.5 times greater than that in the single-task experiment to achieve a power of 0.8. In other words, with a probability of one in six spontaneous initiators in the single-task experiment, we can only detect a difference between the single- and dual-task experiment proportions if at least two in three participants in the dual-task experiment were spontaneous initiators, which we did not find. On average, during the First Experience Period our spontaneous initiators converged to a step frequency lower than their initial preferred step frequency (−3.77±1.31%, $P=0.038$). In contrast, non-spontaneous initiators remained at a step frequency that was not different from their initial preferred step frequency during this First Experience Period (−1.39±2.25%, $P=0.122$). We conducted all subsequent analyses on eight participants from the dual-task experiment and 14 participants from the single-task experiment.

Tone discrimination task requires explicit attention

Our secondary tone discrimination task was cognitively challenging, demanding attention and explicit processing. We found that even during the Baseline Period, when the exoskeleton controller was off and the energy optima unchanged, participants made response errors. On average, response accuracy was 91.4±6.2%, which is better than chance (50%) but not perfect (100%) (Fig. 3A). Moreover, we found that participants' reaction times were more than three times that typically reported for a simple button press in the absence of a tone discrimination task [0.901±0.073 s (present study) versus 0.247±0.014 s (Stuss et al., 1989), $P=1.9\times10^{-8}$; Fig. 3B], indicating that the task demanded significant explicit processing.

Tone discrimination task performance was unaffected by the energy optimization process

Participants' performance on the secondary tone discrimination task did not worsen when the primary energy optimization task was presented. We found no differences in accuracy scores calculated during the Baseline Period, when the exoskeleton was turned off, and the Second Experience Period, when the exoskeleton was turned on and the energy optima changed (91.4±6.2% versus 86.4 ±14.7%, respectively; $P=0.221$; Fig. 3A). The same was true for reaction time scores (0.901±0.073 s versus 0.872±0.086 s, respectively; $P=0.397$; Fig. 3B). Similarly, performance on the secondary tone discrimination task did not worsen when the metronome was on. We found that the average accuracy scores were not different when the metronome was or was not on (82.6±7.0% versus 85.6±11.1%, $P=0.321$).

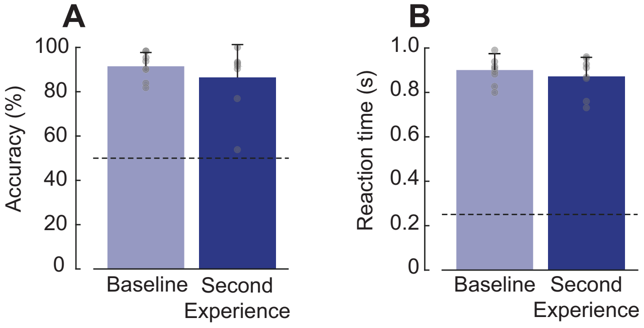

Fig. 3. Secondary tone discrimination task performance. (A) Average accuracy score (%) during the Baseline Period (light blue) and Second Experience Period (dark blue). The dashed horizontal line represents chance (50% accuracy). (B) Average reaction time (s) during the Baseline Period (light blue) and Second Experience Period (dark blue). The dashed horizontal line represents average reaction time (0.247 s) for a simple button press task in the absence of a tone discrimination task (Stuss et al., 1989). Error bars represent one standard deviation. Circles represent individual data from each participant ($n=8$).

Tone discrimination task does not prevent the energy optimization process

Participants adapted their gait to reduce energy expenditure, despite the demands of the secondary tone discrimination task. We found that participants adapted toward the energy optima, displaying a final preferred step frequency that was lower than their initial preferred step frequency (−3.8±3.5% versus 0%, $P=0.010$; Fig. 4). Moreover, the magnitude of this adaptation was similar to that for the single-task experiment (−4.02±4.2%, $P=0.880$). Furthermore, participants de-adapted to a step frequency that was not different from their initial preferred step frequency (0%) when the exoskeleton was turned off and they were returned to a natural cost landscape (−1.01±2.3% versus 0%, $P=0.262$). We found high variation in the individual participants' adaptation and de-adaptation rates, with no discernible differences between the single- and dual-task experiments (adaptation rate: 25.6±18.4 s versus 41.7±7.6 s, respectively, $P=0.219$; Fig. S1A; de-adaptation rate: 15.4±12.1 s versus 18.7±12.1 s, respectively, $P=0.610$, Fig. S1B).

Tone discrimination task disrupts explicit awareness of the energy optimization process

The presence of a secondary explicit task disrupted participants' awareness of their gait adaptation and perception of control over the exoskeleton during the primary energy optimization task. We found that raters' average scores of participant awareness in our dual-task experiment were lower than those in the single-task experiment for questions 1–3 (0.1±0.2 versus 2.9±2.0, $P=6.6\times10^{-4}$; 0.4±1.2 versus 2.5±2.3, $P=0.019$; 1.9±2.4 versus 4.3±2.1, $P=0.027$; Fig. 5A). For these questions, average scores for our dual-task experiment indicated no to low levels of awareness (scores between 0 and 2), while those for the single-task experiment indicated moderate levels of awareness (scores between 2.5 and 4.5). We found similar differences for raters' average scores of participant control for

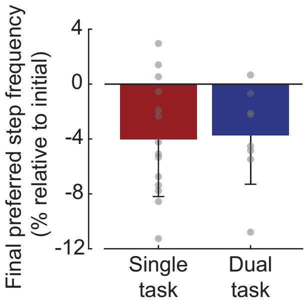

Fig. 4. Average final preferred step frequency for participants in the single-task and dual-task experiments (red and blue bars, respectively). Error bars represent one standard deviation. Circles represent individual data from each participant in the single-task and dual-task experiments ($n=14$ and $n=8$, respectively).

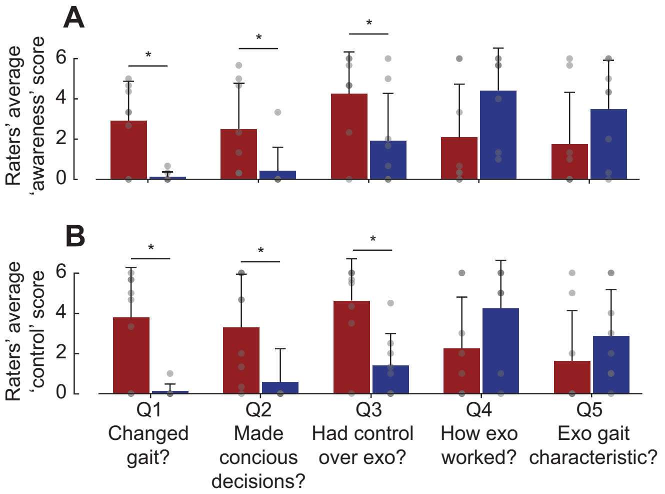

Fig. 5. Survey results. (A) Raters' average scores of participant awareness. (B) Raters' average scores of participants' perception of control. Red bars represent single-task participants and blue bars represent dual-task participants. Error bars represent one standard deviation. Circles represent individual data from each participant in the single-task and dual-task experiments (*n*=14 and *n*=8, respectively).

questions 1–3 (0.1±0.4 versus 3.8±2.5, P=5.0×10^{-4}; 0.6±1.6 versus 3.3±2.6, P=0.014; 1.4±1.6 versus 4.6±2.1, P=0.002; Fig. 5B). For these questions, average scores for our dual-task experiment indicated no to low levels of control (scores between 0 and 1.5), while those for the single-task experiment indicated moderate to high levels of control (scores between 3 and 5). There were no differences in awareness or control scores between dual-task and single-task participants for questions 4 and 5 (Fig. 5A,B).

DISCUSSION

We used a dual-task paradigm to probe the contributions of implicit and explicit processes in energy optimization during walking. We found that adding a secondary, cognitively demanding, explicit task does not prevent optimization. Participants in our dual-task experiment showed adaptation magnitudes and rates similar to those of participants in our previous single-task experiment, where attentional resources were not shared with another task. We also found that performance on the secondary tone discrimination task did not worsen when participants were adapting toward energy optima; accuracy scores and reaction times remained unchanged when the exoskeleton altered the energy optimal gaits. Additionally, the survey responses suggest that dual-task participants were distracted by the secondary task; they were largely unaware of the changes they made to their gait to adapt toward energy optima or the control they had over the exoskeleton. Interestingly, although single-task participants scored higher for both their awareness of gait change and perception of control, they adapted their step frequency to the optima by the same magnitude as those in the dual-task. This suggests that even when explicit awareness exists, it may not affect one's ability to discover the energy optima. Collectively, our results suggest that energy optimization during walking involves implicit processing, and likely requires minimal explicit attention.

The primary limitation of our experiment is our inability to detect partial changes in the magnitude of adaptation between single- and dual-task participants. We found that the magnitude of step frequency adaptations was similar between dual- and single-task experiments – we found no statistical differences. However, variability in individual step frequency measures is high, and although we had the power to detect a full disruption of adaptation (0% versus 5%), we lacked the statistical power to detect smaller, partial changes. To gain a better intuitive sense of the conclusions to be drawn from our results, we conducted a *post hoc* probability analysis to determine the probability of various step frequency differences (between 0 and 5%) truly existing in the population. To do so, we simulated step frequency adaptations for both the dual- and single-task groups that are drawn from normal distributions with standard deviations set to 3.5% and 4.2%, respectively, matching that from our experimental data. We also set the sample sizes to match those in our experiments (n=8 for dual-task and n=14 for single-task). We set the mean of the single-task distribution to −5% (roughly equivalent to that seen in single-task experiment) and then varied the mean of the dual-task distribution between 0 and −5% by 0.5% increments. For each increment, we performed 100,000 iterations. To obtain the probability of our actual experimental outcome (0.22% difference between dual- and single-task step frequency adaptation magnitudes), we summed the number of iterations where the difference was greater than 0.22% and divided that by the total number of iterations. We found that the probability of our outcome (0.22% difference or less between single- and dual-task participants) is less than 1 in 500 if a difference of 5% truly existed in the population, as would be the case if exclusively explicit processing was used in energy optimization. This probability increases to 1 in 12 if a difference of 2.5% truly existed, in the case that explicit and implicit processes made equal contributions, and 1 in 3 if a difference of 1% truly existed, in the case of a predominately implicit process. Our results indicate that in our experiment energy optimization involved implicit processing, but we are unable to determine whether minor explicit contributions existed and were disrupted.

Other limitations of our experiment are inherent to dual-task paradigms. First, it is difficult to know, with certainty, whether our participants were sufficiently distracted by the secondary tone discrimination task. The average accuracy scores (>85%) of participants were higher than we expected from piloting. If our secondary task was not challenging enough, it is possible that participants had the attentional resources necessary to simultaneously carry out the primary energy optimization task using an explicit process, without displaying performance decrements on either task. However, our survey results suggest this was likely not the case. Dual-task participants were less aware of their gait changes and their ability to affect the exoskeleton behaviour, indicating that they were meaningfully distracted by the secondary task. A second potential interpretation of our findings is that our two tasks draw on distinct cognitive 'resource pools'. The central-resource capacity theory suggests there is a single source of attentional resources for which all simultaneous activities compete; for example, walking and having a conversation with a friend (Kahneman, 1973; Magill, 2011; Schmidt and Lee, 2011). Alternatively, multiple-resource capacity theory suggests there are several resource pools, each with limited capacity, and each specific to different tasks or processing stages (Magill, 2011; Wickens, 2002). It is possible that our primary energy optimization task and secondary tone discrimination task draw from two different resource pools, in which case we would not expect performance decrements in either task. Again, however, the lower survey scores of dual-task participants suggest that any cognitive awareness of the primary optimization task, whether used to optimize or not, draws from the same pool of resources as our tone discrimination task. Moreover, previous findings, in walking and reaching adaptation paradigms, suggest that tone discrimination tasks can compete for the same resources as these motor tasks (Conradsson et al., 2019; Malone and Bastian, 2010; Taylor and Thoroughman, 2007). While not possible to conclusively rule out these alternative interpretations, or a minor contribution from an explicit process, our experimental and survey results in combination suggest that energy optimization involves implicit processing.

Our distraction task appears to have disrupted participants' explicit awareness of gait adaptation, but may not have fully abolished their understanding of the exoskeleton controller. Our first three survey questions (Q1–3) focused on understanding whether participants were strategically changing how they walked and whether they could verbalize this strategy (Did you change how you walked? Did you make conscious decisions? Did you feel you had control?). Dual-task participants scored very low on these questions (average scores less than two), and scored significantly lower than those in the single-task experiment (average scores greater than 2.5). Our last two survey questions (Q4–5) focused on understanding whether participants understood how the exoskeleton controller worked (How did the exoskeleton make walking easier or harder? What gait characteristic affected what the exoskeleton was doing?). Here, dual-task participants' average scores were higher than for previous questions (average scores greater than 3), although we found no significant difference compared with single-task participants. This suggests that in the presence of the secondary tone discrimination task, participants may still have some explicit understanding of how the exoskeleton controller works, but may not be able to simultaneously develop an explicit gait strategy in response (Bronstein et al., 2009). Single-task participants, who were not distracted and therefore had additional attentional resources, did appear to be able to articulate an explicit gait strategy. That this explicit strategy did not lead to better performance on the energy optimization task – the magnitude and rate of gait adaptation in single-task and dual-task participants was similar – further suggests the process of energy optimization itself is not exclusively explicit.

Our findings are consistent with prior work demonstrating that locomotor adaptations that drive learning are remarkably invariant and unaffected by explicit processes. One approach to understanding the role of conscious control in gait is to disrupt participants' explicit strategy formation, through a secondary task, and see whether this distraction will diminish gait adaptation (as we have done here). An opposite approach is to give participants an explicit strategy, often through direct feedback about the errors they need to reduce, and to see whether this awareness will enhance gait adaptation. Malone and Bastian (2010) used both approaches to investigate the role of conscious, or explicit, gait corrections during adaptation to a split-belt treadmill. They found that distraction slowed the rate of adaptation while conscious correction sped it up. However, after-effects during de-adaptation lasted the longest following distraction, indicating that gait adaptation was more engrained, or better learned, despite the slower adaptation rate. Roemmich et al. (2016) extended this work and demonstrated that explicit information about errors during split-belt walking can lead to rapid and substantial improvements in motor performance without any true improvements in learning. They showed that when explicit feedback is removed, participants revert to a level of gait adaptation consistent with that expected based on rates of adaptation from implicit, in their case proprioceptive, sources. In other words, one can make conscious changes to their gait, based on explicit feedback about errors, but this is not retained and does not improve learning in novel contexts. The finding that voluntary corrections are mechanistically distinct from implicit adaptation and learning is consistent with prior models of gait response to perturbation proposing two processes – one rapid but approximate based on prediction and one slow but accurate driven by optimization (O'Connor and Donelan, 2012; Snaterse et al., 2011). That we found no difference in adaptation or de-adaptation between our dual- and single-task experiments implies that in our paradigm, implicit optimization is dominant. However, our findings with respect to adaptation and de-adaptation rates are variable and our sample sizes low (n=3–4 and n=8–14, respectively), and should be interpreted with caution. It is possible that in other gait adaptation paradigms, such as the split-belt, explicit predictions are more evident because the task is more visually or kinematically clear. The more complex and closed-loop nature of our exoskeleton controller may have prevented rapid explicit prediction. In future, providing participants with explicit feedback about energy costs could offer additional insight into the energy optimization process and serve as an added test of its implicit nature.

That energy optimization involves implicit processing has both potential benefits and drawbacks for an adapting human. One clear advantage is that attentional resources can be directed toward other movement objectives. For example, cognitive attention during walking can be directed toward accuracy and navigation demands when encountering obstacles. These explicit demands may act as constraints, while energy optimization proceeds implicitly within these bounds. Another advantage is that when energy optimal solutions are complex and difficult to explicitly predict, the implicit system may work in the background to navigate them over sufficient timescales. This may well be the case when people are adapting to injuries that change body mechanics and neural control, or when adapting to assistive devices that apply novel forces and alter limb dynamics, as we did here. While a therapist or prosthetist may be unable to coach an individual to an energy optimal coordination pattern, the nervous system of the individual may implicitly learn this over time. However, implicit energy optimization may also have unfavourable consequences. Although gait rehabilitation strategies often focus on restoring a desired 'normal' or 'healthy' gait, our implicit optimization process may be at odds with these kinematic goals if the gaits are no longer energy optimal following injury (Roemmich et al., 2019). A focus on aligning these otherwise competing objectives may lead to more effective and enduring rehabilitation. Another possible disadvantage of implicit optimization is that many have found adaptation that relies solely on an implicit process will be incomplete – residual errors and asymptotic offsets persist even after many trials (Albert et al., 2021; Bond and Taylor, 2015). Albert et al. (2021) demonstrated that this offset is a signature of implicit, error-based learning and its magnitude relates to one's sensitivity to past errors. Although error-based learning and energy optimization are often considered two separate processes, they may ultimately be driven by the same cognitive objectives and lead to similar movement outcomes. For example, reductions in energetic cost have been demonstrated as participants adapt their reaching movements to both force fields (Huang et al., 2012) and visuomotor paradigms (Huang and Ahmed, 2014), suggesting that minimizing energy and minimizing error may each be an objective in the same adaptive process. In our experiment, our inability to precisely identify the energy optimal gait makes it difficult to determine whether adaptation was incomplete. However, in some of our past work, partial adaptation toward energy optimal gait is clear, further implicating an implicit process during energy optimization (Abram et al., 2019; Simha et al., 2019).

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Competing interests
The authors declare no competing or financial interests.

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