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Alteration of brain dynamics during dual-task overground walking

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Abstract

When walking in our natural environment, we often solve additional cognitive tasks. This increases the demand of resources needed for both the cognitive and motor systems, resulting in Cognitive-Motor Interference (CMI). A large portion of neurophysiological investigations on CMI took place in static settings, emphasizing the experimental rigor but overshadowing the ecological validity. As a more ecologically valid alternative to treadmill and desktop-based setups to investigate CMI, we developed a dual-task walking scenario in virtual reality (VR) combined with Mobile Brain/Body Imaging (MoBI). We aimed at investigating how brain dynamics are modulated by dual-task overground walking with an additional task in the visual domain. Participants performed a visual discrimination task in VR while standing (single-task) and walking overground (dual-task). Even though walking had no impact on the performance in the visual discrimination task, a P3 amplitude reduction along with changes in power spectral densities (PSDs) were observed for discriminating visual stimuli during dual-task walking. These results reflect an impact of walking on the parallel processing of visual stimuli even when the cognitive task is particularly easy. This standardized and easy to modify VR paradigm helps to systematically study CMI, allowing researchers to control for the impact of additional task complexity of tasks in different sensory modalities. Future investigations implementing an improved virtual design with more challenging cognitive and motor tasks will have to investigate the roles of both cognition and motion, allowing for a better understanding of the functional architecture of attention reallocation between cognitive and motor systems during active behavior.

KEYWORDS

cognitive-motor interference, EEG, MoBI, natural cognition, virtual reality

1 **INTRODUCTION**

In our daily activities, we often need to walk while interacting with our environment in order to meet everyday goals. Walking requires the processing of both external and internal sensory information that help maintain action goals, reacting

to changing environmental features, and readapting motor programs anytime unexpected events occur. Therefore, despite often perceived as undemanding, walking involves both sensory and cognitive systems (Hausdorff, Schweiger, Herman, Yogev-Seligmann, & Giladi, 2008; Woollacott & Shumway-Cook, 2002). During walking, our limited attentional resources have to be distributed between the motor and cognitive tasks,

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potentially causing a cognitive-motor interference (CMI) (for a review, Al-Yahya et al., 2011). This phenomenon has been widely investigated through dual-task walking paradigms and is indicated by a performance deterioration in the cognitive and/or in the motor task. In the motor domain, decreased walking speed and increased stride time and variability were often observed (Beurskens, Steinberg, Antoniewicz, Wolff, & Granacher, 2016; De Sanctis, Butler, Malcolm, & Foxe, 2014; Malcolm, Foxe, Butler, & De Sanctis, 2015; Patel, Lamar, & Bhatt, 2014; Pizzamiglio, Naeem, Abdalla, & Turner, 2017; Plummer, Apple, Dowd, & Keith, 2015). Particularly for additional visual tasks during walking, increased response times and higher error rates were registered (Beurskens et al., 2016; Patel et al., 2014; Plummer et al., 2015).

Recently, the neural foundations of dual-task walking have been addressed through Mobile Brain/Body Imaging (MoBI; Gramann, Ferris, Gwin, & Makeig, 2014; Gramann et al., 2011; Makeig, Gramann, Jung, Sejnowski, & Poizner, 2009). MoBI has been proposed as a method for imaging brain dynamics during active movement, allowing to gain deeper insights into the interplay of motor and cognitive processes. The general feasibility of the MoBI concept has been demonstrated and applied to dual-task walking scenarios (e.g., Bradford, Lukos, Passaro, Ries, & Ferris, 2019; De Sanctis, Butler, Green, Snyder, & Foxe, 2012; De Sanctis et al., 2014; Debener, Minow, Emkes, Gandras, & De Vos, 2012; Gramann, Gwin, Bigdely-Shamlo, Ferris, & Makeig, 2010; Ladouce, Donaldson, Dudchenko, & Ietswaart, 2019; Pizzamiglio et al., 2017; Reiser, Wascher, & Arnau, 2019). However, particularly when investigating dual-task walking using secondary tasks that tax the visual modality, a large portion of mobile neurophysiological investigations on CMI took place in artificial settings that used treadmill and fixed desktop setups. Only a few studies investigated the brain dynamics during overground walking but never in the visual domain (Debener et al., 2012; Ladouce et al., 2019; Pizzamiglio et al., 2017; Reiser et al., 2019). During natural overground walking, however, visual input is crucial when scanning the upcoming path and avoiding falls or collisions (Imai, Moore, Raphan, & Cohen, 2001; Nomura, Mulavara, Richards, Brady, & Bloomberg, 2005). Moreover, visual scanning of the surrounding relies on and thus competes with the same resources that are necessary for performing secondary visual tasks (Wickens, 2002). Therefore, it is necessary to replace static setups with more realistic but controlled paradigms that better represent the central role of visual information for controlling ongoing gait and planning future movement in a changing environment.

1.1 **Neural indicators of CMI**

Studies on event-related potentials (ERPs) investigating CMI mainly focused on the investigation of the P3 component,

which is sensitive toward the amount of attentional resources engaged to solve a task (Isreal, Chesney, Wickens, & Donchin, 1980a; Isreal, Wickens, Chesney, & Donchin, 1980b; Polich, 2007). In a pioneering work, Gramann et al. (2010) analyzed the brain dynamics of participants during standing, slow, and fast treadmill walking, while attending to a visual oddball task. They demonstrated that the oddball P3 known from traditional desktop scenarios can be replicated in paradigms allowing active walking. For the auditory domain, several studies demonstrated reduced posterior P3 components when walking compared to standing or sitting reflecting reduced availability of resources for the cognitive task (e.g., Debener et al., 2012; Ladouce et al., 2019; Reiser et al., 2019). To examine CMI in the visual domain, De Sanctis et al., (2014) observed a robust reduction in the P3 amplitude at centro-parietal regions in a visual Go/NoGo task during treadmill walking as compared to sitting. In the same condition, they observed a shorter P3 latency indicating an earlier onset of the processes related to the P3 when walking. These findings suggested that, for increasing task load, more conscious and effortful processing strategies were employed and a flexible redistribution of cognitive resources between the cognitive and motor tasks occurred. Moreover, a significant increase in P3 amplitudes was reported over fronto-central regions when walking briskly as compared to sitting, which was interpreted as an additional engagement of prefrontal resources to cope with the more cognitively effortful situation. In a follow-up study, shorter P3 latency and decreased P3 amplitudes were reproduced in young participants performing a visual Go/NoGo task while walking compared to sitting (Malcolm et al., 2015). In this study, a topographical shift of the P3 toward more fronto-central sites was observed only in older participants. This finding was interpreted to reflect enhanced cognitive control by recruiting additional frontal areas to compensate for an age-related cognitive decline.

This kind of resource redistribution during dual-task walking has also been associated with changes in the frequency domain. Several studies described theta (4-7 Hz) power increase and alpha (8-12 Hz) power decrease during treadmill walking (Presacco, Goodman, Forrester, & Contreras-Vidal, 2011; Wagner, Solis-Escalante, Scherer, Neuper, & Müller-Putz, 2014; Seeber, Scherer, Wagner, Solis-Escalante, & Müller-Putz, 2014; Beurskens et al., 2016; Peterson & Ferris, 2018; but see Malcolm et al., 2015, reporting no differences). In particular, Peterson and Ferris (2018) investigated brain patterns related to balance perturbations while standing and walking on a treadmill and interpreted the higher theta power observed in their walking condition as an indicator for increasing balance difficulty. Furthermore, the alpha power decrease over sensorimotor areas during walking was interpreted to reflect differences in motor readiness, indicating that a more cognitively engaging task was performed.

Similarly, Beurskens et al. (2016) observed a decrease in alpha power over fronto-central brain areas while walking on a treadmill associated with both cognitive and motor perturbations. The authors interpreted this modulation as a function of an increased cognitive load during dual-task walking. In the higher frequency ranges, beta (12-30 Hz) power was demonstrated to have a role in attention-related processes for numerous thalamic and cortical centers of the visual system (Wróbel, 2000 for a review). In mobile participants during walking, beta suppression was reported to play a role in walking reflecting the motoric activity as an "active state" of the brain (Engel & Fries, 2010; Pizzamiglio et al., 2017; Seeber et al., 2014; Wagner et al., 2014). Paradigms contrasting treadmill walking with a non-movement condition revealed upper beta rhythms (>18 Hz) to be suppressed during the whole gait cycle as a function of the activation of sensorimotor areas (Presacco et al., 2011; Seeber et al., 2014). When comparing a single walking condition with diverse secondary tasks, a beta power increase was also observed both for higher motor and cognitive demands. Particularly, beta power increased over frontal regions (Beurskens et al., 2016) for a secondary motor task (holding two interlocked sticks) as compared to a secondary cognitive task (Go/NoGo task). Gamma power (>30 Hz) was shown to increase with greater postural instability (Slobounov, Cao, Jaiswal, & Newell, 2009) and has been related to muscle activation during upper and lower limb movements (Brown, 2000; Mima, Steger, Schulman, Gerloff, & Hallett, 2000; Raethjen et al., 2008). Gait cycle-dependent modulations in the gamma band have been reported over the frontal, central, and parietal cortex of healthy walking adults (Gwin, Gramann, Makeig, & Ferris, 2011). A tonic increased power in gamma frequencies was reported for walking when compared to standing (Peterson & Ferris, 2018) and for waking and performing a serial subtraction task compared to walking only (Marcar, Bridenbaugh, Kool, Niedermann, & Kressig, 2014), demonstrating that gamma modulations arise not only from motor activity itself but also from the execution of additional tasks while walking.

1.2 | Dual-task overground walking with tasks in the visual domain

The above-reported studies imply CMI for dual-task walking for a variety of additional cognitive tasks. The findings document a flexible re-deployment of attentional resources between the cognitive and the motor task when concurrently performed. However, most of the previous studies were conducted with treadmills and fixed displays, which allow for an accurate understanding of gait kinematics but are not ecologically valid. For instance, during treadmill walking, participants have to match their gait velocity to the speed of the treadmill to secure their position. Natural overground EIN European Journal of Neuroscience FENS

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walking, in contrast, allows for varying walking speed and requires visual scanning of the upcoming terrain (Marigold & Patla, 2008). Therefore, it is associated with orienting movements of the head and eyes that are absent when participants do not scan for relevant information in their environment. Moreover, real-world situations require divided attention over a wide area of the visual field decreasing detection and discrimination accuracy for increasingly eccentric information (Carrasco, Evert, Chang, & Katz, 1995; Staugaard, Petersen, & Vangkilde, 2016). Increasing resource demands when walking might thus lead to decreasing detection accuracies for more eccentric visual information. Therefore, investigating the neural dynamics associated with more natural overground walking with ecologically valid visual scanning behaviors will provide new insights into the brain dynamics contributing to the foundation of human dual-task walking behaviors.

To overcome the restriction of previous studies, we coupled virtual reality (VR) and mobile EEG to allow for investigation of CMI during more ecological valid dual-task overground walking with the requirement to process additional visual information. In particular, we simulated an evervday situation through VR in which people stood or walked freely while discriminating and responding to external visual stimuli appearing at different eccentricities. We expected higher perceived subjective mental load when walking with an additional visual task as compared to standing, accompanied by a decrease in performance for the visual discrimination task (Beurskens et al., 2016; Patel et al., 2014; Plummer et al., 2015). Performance deterioration in the visual task was expected to be most pronounced for more peripherally as compared to more centrally presented visual stimuli (Carrasco et al., 1995; Staugaard et al., 2016) in the dual-task condition. Regarding the physiological responses, we expected an earlier onset and a lower amplitude of a centro-parietal P3 component evoked with visual stimuli reflecting a reallocation of cognitive resources in the dual-task condition (De Sanctis et al., 2014; Malcolm et al., 2015). For the frequency domain, we expected higher theta and lower alpha power in the dual-task condition (Beurskens et al., 2016; Peterson & Ferris, 2018) along with changes in the beta rhythms and increased gamma power (Gwin et al., 2010; Marcar et al., 2014; Pizzamiglio et al., 2017; Presacco et al., 2011).

2 | MATERIALS AND METHODS

2.1 | Participants

Right-handed participants (n = 25) with normal or corrected to normal vision as well as normal color vision were recruited to take part in the experiment. All participants reported to be in good health and free of any

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neurological conditions. They also reported the absence of medication containing psycho/neuroleptics or use of intoxicants (alcohol, coffee, cigarettes) within the last 24 hr prior to the experiment. Due to a misconnection of the technical apparatus, three participants were excluded from the analysis. The remaining sample included data from 22 participants: 6 women (age range: 20-31 years, M = 25.5, SD = 3.92) and 16 men (age range: 21–34 years, M = 27.2, SD = 4.48). Before the experiment, participants were asked to report their height in centimeters for adapting the virtual environment (height range for women: 170-172 cm, M = 170.33 cm, SD = 0.83 cm; height range for men: 170-181 cm, M = 174.38 cm, SD = 4.15 cm). Specifically, the height of all the virtual objects was adapted and fixed to the height of the participant (right above the eye level) and not to the headset, such that the virtual environment was not affected by head movement during locomotion. Only right-handed participants were recruited, and the walking direction was chosen to be counterclockwise in order to avoid possible effects of handedness on the turning behavior (Karim, Proulx, & Likova, 2016; Mohr & Bracha, 2004). The study was approved by the TU Berlin ethics committee. All participants were recruited through the local online participant portal, gave written informed consent, and obtained academic credits for compensation.

2.2 **Technical setup**

To investigate the neural correlates of CMI, we implemented a MoBI approach using the setup shown in Figure 1. It consisted of a 128 channels EEG MOVE system (Brain Products GmbH), in combination with acti-CAP (Easycap GmbH), and a VR headset (ACER WMR; 2.89", 2,880 x 1,440 resolution, refresh rate of 90 Hz, 100° field of view with a weight of 440 g). The headset was tethered to a Zotac gaming computer (Zotac PC, Intel 7th Gen Kaby Lake processor, GeForce GTX 1,060 graphics, 32GB DDR4-2400 memory support, Windows 10 OS) placed in a backpack. The Zotac system was extended with two batteries that allowed swapping them approximately after three blocks of experimental session (circa 40 min) without shutting down the VR. Participants were projected into a virtual environment (VE) designed in Unity (2017.3). In addition, a prototype of VR-EEG adapters (Wenzel, 2018) was used to reduce the mechanical pressure on frontal and occipital channels of the EEG cap induced by the VR goggles. The adapters further increased the signal-to-noise ratio by reducing headset movements accompanying locomotion. Both behavioral and neural data streams were synchronized via Lab Streaming Layer (Kothe, 2014).



FIGURE 1 Overview of the technical setup for the MoBI experiment. The participant was equipped with a 128-channel EEG MOVE system and a VR headset (ACER Windows Mixed Reality) tethered to a Zotac gaming computer placed in a backpack. Moreover, two Windows Mixed Reality controllers were used for responding to the lateralized virtual stimuli

Experimental procedure 2.3

The experiment took place at the Berlin Mobile Brain/Body Imaging Laboratories (BeMoBIL), with a dedicated room providing an experimental space of 150 m² for participants to move around without restrictions. The virtual space provided an elliptical path that was 10.8 m long and 2.5 m wide. Data collection took place in one single experimental session. During the training phase, participants were asked to walk along the oval path and to follow a red moving sphere (Figure 2). Prior to the experiment, each participant was able to adjust the speed of the sphere to their preferred natural walking pace using the controller in a training session. The speed was then kept constant during the experiment. When moving the head away from the virtual sphere, the sphere stopped moving and changed its color to black until participants turned their heads back in line with the sphere. In this way, we controlled for participants' head orientation and walking speed. In the second part of the training phase, participants were instructed to follow the sphere while



FIGURE 2 First person view of the participant. A red sphere is placed centrally on the path controlling the walking pace. Next to it, two examples of targets for the visual discrimination task are shown: in the *Left* hemifield the *Yellow* target, in the *Right* hemifield the *Blue* target. Targets could appear in a randomized fashion in the left and right hemifield and at 15° or 35° of eccentricity at the same height of the participant. On the left, an illustration of the checkpoint that participants had to reach for starting the experiment

performing a visual discrimination task. This part consisted of 15 trials with the aim of familiarizing with the task and the virtual environment.

2.4 | Experimental design

In the main experiment, participants performed a visual discrimination task while walking or standing with the movement conditions alternating in six blocks. The initial movement condition was counterbalanced across participants; half of the participants started with the standing condition first while the other half started with the walking condition. Each block consisted of 240 trials displaying visual targets at different eccentricities while participants walked around the elliptoid path. Overall, 720 targets were presented per movement condition with a total of 1,440 targets per participant. Between each block, participants were asked to take a break, allowing them to sit down for a few minutes, and to flip-up the VR headset. As the headset display could be flipped up without moving the headset position on the head, the position of electrodes was not affected.

As illustrated in Figure 2, a virtual green field was used as the background. The red sphere, controlling for the subject's walking speed, was placed centrally on the grey path and participants were instructed to keep their gaze toward the sphere at all times to reduce head movement. A yellow cube (*Yellow* condition) or a blue cube (*Blue* condition) were presented for 200 ms in the left (*Left* condition) or in the right (*Right* condition) hemifield at 15° or 35° eccentricity (*15°* and *35°* condition, respectively). Target color, hemifield and eccentricity were randomized and counterbalanced. Participants had to press the trigger on the right controller whenever a blue cube was presented and the trigger on the left controller when a yellow cube appeared. If participants responded correctly within a 1.5 s time interval after stimulus presentation, the response was registered as 'correct'; if an incorrect trigger was pressed, it was registered as 'incorrect' and if none of the triggers were pressed, the response was classified as 'missed'. After each response, a 2000 ms time window elapsed before the presentation of the next stimulus. Task and instructions were identical for both the standing and the walking phase.

2.5 | EEG recording and preprocessing

EEG recordings were conducted with an actively amplified 128-channel mobile EEG system (MOVE; Brain Products), with a sampling frequency of 1,000 Hz. Two EOG electrodes were placed under each eye to measure vertical eye movements and EEG electrodes were placed equidistant according to a custom layout (Figure 4). Reference and ground electrodes were placed over posterior leads, close to the standard P1 and P2 locations, respectively. Impedances of all scalp electrodes were kept below 10 Kohm. Raw data were processed offline using MATLAB R2018a (MathWorks) and EEGLAB 14.1.2b toolbox (SCCN, University of California, 2018). All preprocessing steps were conducted using the BeMoBIL Preprocessing Pipeline (Klug, 2019) which specifically aims to generalize and simplify the processing of continuous EEG data acquired from MoBI experiments. A schematic overview of the preprocessing pipeline can be found in Figure 3.

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The raw EEG data were first filtered to the range of 0.2 Hz and 90 Hz using a finite impulse response (FIR) filter with zero phase and resampled to 250 Hz. Subsequently, bad channels were identified and removed by automated rejection using kurtosis (the threshold was set to 5 standard deviations (SDs) from mean kurtosis) and probability functions (with a threshold of 3 SDs from mean probability distribution). Removed channels were interpolated with spherical interpolation and data were subsequently re-referenced to the average reference. This "precleaned" dataset was screened for additional spikes and other artifacts (e.g., muscle activity, noise) by visual inspection. Then, for the identification and removal of eye blink artifacts, we utilized the procedure of adaptive mixture independent

component analysis (AMICA, Hsu et al., 2018; Palmer, Kreutz-Delgado, & Makeig, 2012). To this end, the raw data were bandpass filtered to 1-90 Hz to improve the decomposition to independent components (ICs) (Winkler, Debener, Müller, & Tangermann, 2015). The resulting decomposition matrices representing the weights and spheres obtained from the AMICA procedure were applied on the "precleaned dataset" (described above) to allow for further component investigation in IC space. ICs representing eve movements (e.g. blinks) were removed based on visual inspection of their component activity as well as component power spectra (Chaumon, Bishop, & Busch, 2015; Makeig, Bell, Jung, & Sejnowski, 1996). Additionally, prior to IC rejection, we performed plausibility testing of



FIGURE 3 Overview of the preprocessing pipeline for the continuous raw EEG data. The pipeline stream starts from the EEG row data and data processing was divided into two separated flows. First, as displayed on the left, the data were preprocessed and then manually cleaned before ICA decomposition. If the decomposition did not reveal clear dipolar components, the additional manual cleaning was done and ICA re-computed. In case of sufficiently clean ICA decompositions, the weights and spheres matrices were copied to the uncleaned dataset that was preprocessed in an identical fashion safe data cleaning, depicted in the right column. Finally, displayed in the middle column, ICs reflecting eye movements were rejected and a low-pass filter of 40 Hz was applied. Delay caused by RDA and Unity software was corrected and stimulus-locked epochs were created for analyzing both ERPs and PSDs



FIGURE 4 Grand mean ERPs and violin distribution of selected P3 amplitudes. In the grand mean ERPs, the shaded area around each component represents the standard deviation, the gray area indicates the 300-600 ms window where the maximum peak was detected, while the yellow area highlights a smaller time window comprising the maximum peak plus and minus 40ms where the amplitude was averaged and used for analysis. Additionally, the solid line indicates the averaged response time in the Single-task, while the broken line in the Dual-task. The subject distributions of the resulting P3 amplitudes are shown in the violin plots on the sides. The customized location of each of the midline channels is indicated in the central headmaps

our IC selection in terms of its equivalent dipole location to be certain that they did not reflect any brain activity. ICs located to the grey matter of the head model were kept (M = 114.18, SD = 3.01) while ICs located outside the gray matter were removed (M = 3.04, SD = 0.82).

After IC removal and back-projection to channel space, the dataset was further low-pass filtered at 40 Hz. Finally, the cleaned continuous dataset was epoched with onset of each visual stimulus with a prestimulus baseline of -200 ms to 1,000 ms after stimulus presentation, and a baseline correction was performed based on the prestimulus interval for each channel and trial. During this step, we additionally accounted for a constant temporal delay of 15 ms that was caused by the Brain Vision RDA interface, the WIFI (MOVE) transmission, and an additional delay resulting from the Unity software which was demonstrated to last 20 ms on average.

2.6 **Statistical analysis**

In the following sections, the standing condition is referred to as "Single-task" condition, and the walking phase is referred to as "Dual-task" condition. Besides differences between Single- and Dual-task (factor: 'Task'), we investigated the potential impact of lateralized stimulus presentation on behavioral and brain responses (factor: 'Hemifield') as well as the potential impact of the target color (factor: 'Target'). Moreover, we investigated the impact of stimulus eccentricity (factor: 'Eccentricity').

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All statistical analyses were conducted using repeated measures ANOVA. When sphericity assumptions were violated in the Mauchly's test of sphericity (Mauchly, 1940), the p-values were adjusted following the Greenhouse-Geisser correction (Greenhouse & Geisser, 1959). Additionally, we performed post hoc tests using the Bonferroni method (Bonferroni, 1936) to correct for multiple comparisons. This statistical procedure was applied to analyze all the dependent measures reported in the results section.

2.6.1 NASA TLX

To investigate the perceived workload, each participant was asked to fill in the NASA TLX (NASA Task Load Index; Hart & Staveland, 1988) questionnaire after the third and the fourth experimental block, thus, after a Single-Task and after a Dual-Task phase, dependent on the initial starting condition. The total workload assessed by the questionnaire was divided into the six subjective subscales ('Items'): mental demand, physical demand, temporal demand, performance, effort, and frustration. We used the questionnaire to assess whether the walking activity had an influence on the subjective mental load. Single items were also analyzed to investigate a potential impact of the movement condition. Therefore, a 2×6 repeated measures ANOVA for factors 'Task' and 'Items' was computed.

2.6.2 Performance

Three $2 \times 2 \times 2 \times 2$ repeated measures ANOVAs were calculated to analyze reaction times, percentage of misses, and percentage of incorrect responses. For all three dependent variables, we tested the same within-subject factors: 'Task' (Single- versus. Dual-task), 'Eccentricity' (15° versus. 35°), 'Hemifield' (Left versus. Right), and 'Target' (Blue versus. Yellow). Reaction times were defined as the time between stimulus onset and button press and analyzed only for correct response trials. Accuracy in task performance was operationalized through the number of missed and incorrect response trials over the total number of trials that remained after artifact correction during the EEG preprocessing. This secured identical trials to enter the performance and EEG statistics. Missed trials were defined as missing responses within the 1.5 s after the stimulus onset, and incorrect trials as a deviation from required response pattern (wrong button response).

2.6.3 **ERPs**

The P3 component evoked by the visual discrimination task was analyzed for the midline electrodes of the custom layout that were closest to the standard midline locations (Figure 4).

These locations are denoted with an apostrophe (Fz', FCz', CPz', Pz', POz', Oz'). From this, the centro-parietal regions, where the P3 maximum is usually observed, as well as brain activity at more frontal and occipital regions were investigated in terms of amplitude and onset time (latency). To this end, the individual maximum peak within a time window from 300 to 600 ms was detected and the P3 amplitude (in microvolts) was computed as the average comprising the maximum peak plus/minus 40ms. To have a more accurate estimate of the P3 peak amplitude, the same procedure was repeated with different amplitude windows (maximum peak ± 10 , 20, 30, and 40 ms). For the final analyses, an 80 ms range (maximum peak ± 40 ms) was chosen as the results revealed the same direction of effects and the longer time window was more suitable for including a relatively smeared P3 component. P3 latency (ms) and amplitude (μ V) means were analyzed in a full-factorial design $(2 \times 2 \times 2 \times 2 \times 6)$ with 'Task' (Single- versus. Dual-task), 'Eccentricity' (15° versus. 35°), 'Hemifield' (Left versus. Right), 'Target' (Blue versus. Yellow), and 'Channel' (Fz', FCz', CPz', Pz', POz', Oz') as repeated measure factors. The effects of the factors 'Channel' and 'Task' are in the focus of the present study and are thus the only effects described in detail in the results and discussion section. However, the complete results are reported in Table S1. In addition, the P3 signal-to-noise ratio (SNR) was calculated for each of the midline channels dividing the amplitude of the ERP maximum in the P3 time range (300-600 ms) by the standard deviation in the prestimulus interval (Debener, Hine, Bleeck, & Eyles, 2008). Finally, 2D reconstructed topographic maps showing the interpolated voltage distribution over 128 electrodes were computed for the P3 time window (300-600 ms) and the ERP voltage activity was averaged across 50 ms time intervals in order to illustrate ERP differences between Task conditions in time.

PSDs 2.6.4

For the Power Spectral Density (PSD) analysis, spectral power ($\mu V^2/Hz$) in the 4–8 Hz (theta), 8–10 Hz (lower alpha), 10-12 Hz (upper alpha), 12-30 Hz (beta), and 30-40 Hz (gamma) band were extracted from the same stimulus-locked epochs used for the ERPs analysis and averaged across each condition. Central midline electrodes (Fz', FCz', CPz', Pz', *POz'*, *Oz'*) were analyzed in a $2 \times 2 \times 2 \times 2 \times 6$ repeatedmeasures ANOVA computed separately for each defined frequency band with the factors 'Task' (Single- versus. Dualtask), 'Eccentricity' (15° versus. 35°), 'Hemifield' (Left versus. Right), 'Target' (Blue versus. Yellow), and 'Channel' (Fz', FCz', CPz', Pz', POz', Oz'). Given our hypotheses, the presentation of results focuses only on the effects of the factors 'Channel' and 'Task' for each of the frequency bands. The complete results are reported in Tables S2 and S3).

$TABLE \ 1 \quad \text{Response time and accuracy rate}$

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Factor	Levels	RT (ms) (Mean ± SD)	N. of incorrect (Mean \pm SD)	% of incorrect (Mean ± SD)	N. of missed (Mean \pm SD)	% of missed (Mean ± SD)
Task	Single-task	501.18 ± 69.7	7.32 ± 7.60	4.19 ± 4.34	1.47 ± 2.69	0.84 ± 1.53
	Dual-task	506.33 ± 79.9	7.23 ± 8.55	4.07 ± 4.74	2.86 ± 6.29	1.65 ± 3.66
Eccentricity	15°	495.75 ± 72.7	6.36 ± 6.64	3.57 ± 3.58	1.34 ± 2.58	0.77 ± 1.45
	35°	511.76 ± 76.6	8.18 ± 9.23	4.69 ± 5.28	2.99 ± 6.31	1.72 ± 3.68
Target \times Hemifield	Yellow Right	522.70 ± 75.9	7.55 ± 8.41	4.35 ± 4.88	2.39 ± 6.34	1.39 ± 3.85
	Yellow Left	500.4 ± 75.85	4.77 ± 3.98	2.68 ± 2.24	2.24 ± 3.62	1.29 ± 2.08
	Blue Left	514.9 ± 72.04	11.8 ± 10.9	6.73 ± 6.01	1.95 ± 3.68	1.14 ± 2.06
	Blue Right	477.01 ± 68.9	4.95 ± 5.12	2.75 ± 2.67	2.08 ± 5.40	1.18 ± 2.99

Note: Conditions highlighted in grey represent incongruent hand-hemifield response.

Abbreviations: N., number; RT, reaction time.

3 | RESULTS

3.1 | Subjective measures

3.1.1 | NASA TLX

A 2x6 repeated-measures factorial ANOVA was computed over the factors 'Task' and 'Items' for analyzing the NASA TLX subscales. The analysis did not yield any significant main effect for 'Task' or 'Items'. Only the interaction between 'Task' and 'Item' was statistically significant $(F_{5,105} = 2.766, p = .031, \eta^2 p = 0.116)$. The data revealed a tendency for higher ratings regarding the mental, physical, and temporal demand in the *Dual-Task* condition while there was a tendency toward higher performance, effort, and frustration scores in the *Single-task* situation. However, corrected post hoc tests did not reveal significant differences between the conditions (*Single-Task* versus. *Dual-Task*) for single items.

3.2 | Performance measures

3.2.1 | Reaction time

The repeated measures factorial ANOVA ($2 \times 2 \times 2 \times 2$) computed for the factors 'Task', 'Eccentricity', 'Hemifield', and 'Target' did not yield a significant main effect of 'Task' on response times. However, a significant main effect for the factor 'Eccentricity' was observed ($F_{1,21} = 99.3$, p < .001, $\eta^2 p = 0.825$) revealing increased reaction times for stimuli appearing at 35° eccentricity as compared to 15° eccentricity. Significant effects were observed also for the factors 'Target' ($F_{1,21} = 8.04$, p = .010, $\eta^2 p = 0.277$) and 'Hemifield ($F_{1,21} = 8.77$, p = .007, $\eta^2 p = 0.295$), and for their interaction ($F_{1,21} = 43.24$, p < .001, $\eta^2 p = 0.673$). Post hoc comparisons for the interaction between 'Target' and 'Hemifield' showed increased reaction times when responding with the left hand to Yellow targets that appeared in the Right hemifield as compared to the same targets that appeared in the Left hemifield (p < .001), and compared to *Blue* targets that appeared in the *Right* hemifield and that were responded to with the right hand (p < .001). Similarly, the reaction time was longer for responses with the right hand to Blue targets when they appeared in the Left hemifield as compared to the same targets when appearing in the *Right* hemifield (p < .001), and to Yellow targets appearing in the Left hemifield (p = .013). Finally, reaction times were about 23ms longer when responding to Yellow targets with the left hand appearing in the Left hemifield compared to responding to Blue targets with the right hand appearing in the *Right* hemifield (p < .001). Reaction time means and standard deviations for 'Task', 'Eccentricity' and 'Target' by 'Hemifield' are reported in Table 1.

3.2.2 Accuracy

Two repeated measures factorial ANOVAs $(2 \times 2 \times 2 \times 2)$ over 'Task', 'Eccentricity', 'Hemifield', and 'Target' were calculated for the percentage of misses and percentage of incorrect responses. The analysis of response accuracy revealed no significant main effect of 'Task' on the percentage of incorrect trials or the percentage of missed trials. However, a significant main effect of 'Eccentricity' for the number of missed targets ($F_{1,21} = 5.94$, p = .024, $\eta^2 p = 0.221$) and incorrect responses ($F_{1,21} = 8.35, p = .009$, $\eta^2 p = 0.285$) was found. A higher percentage of incorrect responses and missed stimuli was observed when stimuli appeared more peripherally as compared to more centrally presented stimuli. Moreover, the analysis of incorrect responses demonstrated a significant interaction between the factors 'Target' and 'Hemifield' ($F_{1,21} = 20.52, p < .001,$ $\eta^2 p = 0.494$). Specifically, significant differences were



FIGURE 5 Topographical distribution of P3 ERP voltage activity across the scalp. The activity was averaged through 50 ms time intervals covering the window of 300-600ms for *Single-* and *Dual-task*. The customized location of the analyzed midline channels is indicated with dots

observed when detecting *Blue* targets (with the right hand) in the Left hemifield as compared to detecting the same targets (with the right hand) in the *Right* hemifield (p < .001) and Yellow targets (with the left hand) in the Left hemifield (p < .001). At the same time, detecting Yellow targets (with the left hand) in the *Right* hemifield led to significantly more incorrect trials as compared to detecting the same Yellow targets (with the left hand) in the *Left* hemifield (p = .036) and Blue targets (with the right hand) in the Right hemifield (p = .007). Finally, detecting Yellow targets with the left hand in the *Right* hemifield yielded a higher percentage of incorrect responses when compared with detecting Blue targets with the right hand in the *Left* hemifield (p = .007). In light of the experimental design, these findings reflect the congruent and incongruent hand-hemifield response trials. Descriptive statistics of response trial numbers and percentages are reported in Table 1.

3.3 | Event-related potentials

3.3.1 | P3 signal-to-noise ratio (SNR)

Results from the SNR calculation show that the SNR was significantly lower for electrode POz' compared to all other midline electrodes (POz'- FCz': p = .04; POz'- CPz': p = .003; POz'- Oz': p = .04) except for channels FCz' (p = .19) and Pz' (p = .24).

3.3.2 | P3 Latency

The means of the P3 latencies (in ms) were analyzed in a repeated measures factorial ANOVA design $(2 \times 2 \times 2 \times 2 \times 6)$ over 'Task', 'Eccentricity', 'Hemifield', 'Target', and 'Channel'. Focusing on the factors of interest for the present

study ('Channel' and 'Task'), a significant main effect was observed only for the factor 'Channel' ($F_{5,105} = 7.11$, p = .003, $\eta^2 p = 0.253$) revealing the shortest P3 latency at Fz' (M = 414.2; SD = 76.1) and increasing latencies at central, parietal, and occipital sites. Post hoc test revealed that the P3 peaked significantly earlier at Fz' as compared to CPz' (M = 438.2; SD = 68.7), Pz' (M = 468.1; SD = 89.1), POz' (M = 477.2; SD = 105), and Oz' (M = 464.3; SD = 83.9; all ps < .001). An earlier P3 maximum was also observed at FCz' (M = 423.6; SD = 75.9) as compared to CPz', Pz', and Oz' (all ps < .001), and at CPz' as compared to Pz', POz', and Oz' (all ps < .001). No significant effect was found for the factor 'Task' ($F_{1,21} = 2.63$, p > .1, $\eta^2 p = .112$) or for its interaction with the factor 'Channel' ($F_{5,105} = 1.4$, p > .2, $\eta^2 p = .063$).

3.3.3 | P3 amplitude

The 2x2x2x2x6 repeated measures factorial ANOVA computed over the factors 'Task', 'Eccentricity', 'Hemifield', 'Target', and 'Channel' yielded significant main effects for the factors 'Channel' ($F_{5,105} = 11.07, p < .001$, $\eta^2 p = 0.345$) and 'Task' ($F_{1,21} = 14.16$, p = .001, $\eta^2 p = 0.403$). These main effects were qualified by their interaction ($F_{5.105} = 4.053$, p = .009, $\eta^2 p = 0.162$). Post hoc test showed significant differences in P3 amplitude between the two tasks for channels CPz' (p = .011), Pz' (p < .001), and Oz' (p < .001). A strong P3 amplitude reduction was observed in all posterior electrodes in the Dual-Task as compared to the Single-task condition (CPz' Single-Task: M = 5.56, SD = 2.29; Dual-Task: M = 5.07, SD = 2.46;Pz' Single-task: M = 3.2, SD = 2.41; Dual-Task: M = 2.62, SD = 2.64; Oz' Single-task: M = 3.96, SD = 2.31; Dual-Task: M = 3.34, SD = 2.13), which can be seen in the topographic changes over time (Figure 5).

In addition, but not in the focus of interest for this study, significant effects were observed also for the factor 'Target' $(F_{1,21} = 5.54, p = .028, \eta^2 p = 0.209)$, for the interaction 'Target' by 'Hemifield' $(F_{5,105} = 5.04, p = .036, \eta^2 p = 0.194)$, and for the three-way interaction between 'Target', 'Hemifield', and 'Task' ($F_{1,21} = 7.6, p = .012, \eta^2 p = 0.266$). As revealed by post hoc comparisons, the differences in P3 amplitude linked to congruent and incongruent hand-hemifield response conditions were observed only in the *Dual-task*. Within this task condition, a lower P3 amplitude was observed when detecting Blue targets in the Left hemifield and responding with the right hand as compared to responding to the same targets in the Right hemifield but had to respond with the right hand (p < .001) and responding with the left hand to Yellow targets that appeared in the *Left* hemifield (p < .001). Finally, responding with the left hand to Yellow targets that appeared in the Right hemifield led to significantly lower P3 amplitudes as compared to responding with the left hand to the same Yellow targets in the Left hemifield (p = .046) and responding with the right hand to *Blue* targets appearing in the *Left* hemifield (p = .005).

3.4 | Power spectral densities

3.4.1 | Theta

A repeated measures factorial ANOVA ($2 \times 2 \times 2 \times 2 \times 6$) over the within-subject factors 'Task', 'Eccentricity', 'Hemifield', 'Target', and 'Channel' was computed for analyzing each defined frequency band. Focusing on the factors of interest for the present study, significant main effects were observed in the theta frequency band (4–8 Hz) for the factors 'Channel' ($F_{5,105} = 12.79$, p < .001, $\eta^2 p = 0.379$) and 'Task' ($F_{1,21} = 39.98$, < 0.001, $\eta^2 p = 0.656$). In addition, a significant interaction effect between 'Channel' and 'Task' was observed ($F_{5,105} = 3.42$, p = .017, $\eta^2 p = 0.140$), revealing a significantly lower theta power in the *Single-task* as compared to the *Dual-Task* condition for all the midline channels Fz' (p < .001), FCz' (p < .001), CPz' (p < .001), Pz'(p < .001), POz' (p < .001), and Oz' (p < .001).

3.4.2 | Lower alpha

Significant results for the factor 'Channel' ($F_{5,105} = 9.05$, p < .001, $\eta^2 p = 0.301$) and for its interaction with the factor 'Task' ($F_{5,105} = 4.59$, p = .011, $\eta^2 p = 0.180$) were found for the lower alpha frequency range (8–10 Hz). Post hoc analysis revealed lower alpha power in the *Dual-Task* condition as compared to the *Single-task* condition, reaching significance at channels *CPz'* (p = .026), *Pz'* (p = .018), and POz' (p < .001) but not Fz', FCz', and Oz'.

3.4.3 | Upper alpha

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In the 10–12 Hz range, significant effects were only found for 'Channel' ($F_{5,105} = 3.62$, p = .018, $\eta^2 p = 0.147$). The interaction 'Channel' x 'Task' also reached significance ($F_{5,105} = 4.2$, p = .014, $\eta^2 p = 0.167$), revealing a significantly lower average power for the upper alpha band in the *Dual-Task* condition as compared to the *Single-task* condition for electrodes *Fz*' (p < .001), *FCz*' (p < .001), *CPz*' (p < .001), and *Pz*' (p = .024).

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3.4.4 | Beta

PSD differences in the beta frequency band (12–30 Hz) were observed, with significant main effects of interest for the factors 'Channel' ($F_{5,105} = 10.72$, p < .001, $\eta^2 p = 0.338$) and 'Task' ($F_{1,21} = 4.6$, p = .044, $\eta^2 p = 0.180$). A significant interaction effect for the same factors also emerged ($F_{5,105} = 9.16$, p < .001, $\eta^2 p = 0.304$). Post hoc tests revealed a significant lower power in the beta band for the *Single-task* as compared to *Dual-Task* for Pz' (p < .001), POz' (p < .001), and Oz' (p < .001), and the opposite trend in CPz' (p < .001).

3.4.5 | Gamma

Power in the gamma frequency band (30–40 Hz) yielded significant main effects for the factors 'Channel' ($F_{5,105} = 14.8$, p < .001, $\eta^2 p = 0.120$) and 'Task' ($F_{1,21} = 21.9$, p < .001, $\eta^2 p = 0.167$), and also for their interaction ($F_{5,105} = 28.05$, p < .001, $\eta^2 p = 0.205$). Post hoc comparisons revealed a significantly higher gamma power when comparing the *Dual-Task* with the *Single-task* conditions for all midline electrodes: Fz' (p < .001), FCz' (p < .001), CPz' (p < .001), Pz' (p < .001), POz' (p < .001), and Oz' (p < .001).

4 | DISCUSSION

The present study was designed to give further insights into the human brain dynamics of dual-task walking, particularly when the cognitive task taxes the same visual resources that are also required for the planning and control of natural overground walking. To this end, we used a visual discrimination task in VR and analyzed the impact of dual-task walking on cognitive performance and brain dynamics using a MoBI approach. The head-mounted VR allowed for a dynamic presentation of stimuli providing higher ecological validity while, at the same time, ensuring control of potential confounding factors which would be present in the real world, including visual and auditory stimuli that are not directly related to the task. In this way we were able to address a relevant aspect of -WILEY-EIN European Journal of Neuroscience FENS

mobile cognition which is resource conflicts during walking when additional stimuli in different areas of the visual field have to be processed.

4.1 | Subjective measures

Our results did not reveal significant differences in the perceived mental load between the Single-task and Dual-Task conditions. Therefore, the overall results from the NASA TLX reflected a comparable workload for the Dual-Task and the Single-task conditions. Only a tendency for higher mental, physical, and temporal demand in the Dual-Task and a tendency toward higher performance, effort, and frustration scores in the Single-task condition were observed. However, none of the single items reached significance when a Bonferroni correction was applied. The absence of any differences experienced in the two conditions might have been due to the secondary task, which, arguably, was particularly easy for the young healthy population under investigation. Nonetheless, it is of interest to point out that even for such a low-demanding cognitive task that did not reveal any distinction in perceived mental load, the brain dynamics revealed systematic task-related differences.

4.2 | Performance measures

The absence of a main effect of the factor 'Task' for all dependent measures of performance likely reflects the relatively low complexity of the additional cognitive task. Interestingly, the 1.65% of missed trials were counted in the *Dual-Task* condition, in contrast to the 0.84% of missed trials observed in the *Single-task* condition (Table 1). Even though this is a clear tendency for a behavioral cost induced by the dual-task walking requirements, this trend failed to reach significance.

The hypothesis regarding the impact of the target eccentricity was supported. Reaction times were significantly slower when responding to stimuli appearing at 35° as compared to 15° eccentricity. In addition, a higher miss rate and a higher rate of incorrect responses were observed for stimuli at 35° eccentricity as compared to those presented at 15° eccentricity. These findings indicate that the position of a salient and attention demanding stimulus can impact visual information processing with higher accuracy and faster responses in the central visual field. Previous studies already demonstrated such an eccentricity effect in vision and attention (Carrasco et al., 1995; Staugaard et al., 2016). Some argue that the effect can be explained by the neurophysiological differences between foveal and peripheral vision (Carrasco & Frieder, 1997). Others state that this could reflect a central bias in the allocation of attentional resources (Brown, Halpert, & Goodale, 2005; Wolfe, O'Neill, & Bennett, 1998).

The eccentricity effect was observed in our novel virtual dual-task walking paradigm as well, proving this approach to replicate more traditional laboratory setups during natural overground walking while contrasting with recent results reported by Cao and Händel (2019).

Additionally, an interaction effect between 'Target' and 'Hemifield' was found both for reaction times and incorrect responses. This can be explained with the Simon effect (Simon, 1969) that predicts increased reaction times and a higher percentage of incorrect responses when targets have to be responded to with an incongruent hand-hemifield response assignment (*Yellow-Right* or *Blue-Left*) as compared to the conditions with congruent hand-hemifield responses (*Yellow-Left* or *Blue-Right*).

4.3 | Event-related potentials

Even though the performance measures did not provide any direct evidence for a main effect of increased effort in the Dual-Task condition, the ERP results clearly indicated differences in neural processing between the Single- and the Dual-Task. Indeed, a significant impact of the 'Task' condition was observed for the P3 amplitude, which decreased in the Dual-Task as compared to the Single-task (Figure 4). These effects differed topographically and were most pronounced over posterior leads (CPz', Pz', Oz'). As indicated by the scalp topographies (Figure 5), the evoked potential reached the maximum voltage over central and posterior areas at 400-500ms in both Single- and Dual-task, with higher positivity in the Single-task. Moreover, the P3 activity appeared to be more sustained in the Single-task, while it rapidly decreased in the Dual-task. These findings replicated previous results on P3 amplitude reductions in dual-task walking scenarios (De Sanctis et al., 2014; Malcolm et al., 2015). In contrast to previous reports, the P3 onset latency did not differ between Single- and Dual-task conditions. Irrespectively to the task load, the latency of the P3 was observed to increase from frontal to occipital sites.

Furthermore, it is important to note that the EEG recordings at POz' were particularly noisy and thus difficult to interpret. The straps of the Mixed Reality goggles were situated precisely over this electrode, likely inducing significant pressure and mechanical noise. This was confirmed by the significantly lower SNR observed at POz' as compared to all other midline electrodes except for channels FCz' and POz'. Moreover, the lower SNR over POz' is consistent with the reduced activity shown in the scalp maps of Figure 5, which covers posterior leads and extends horizontally in both hemispheres, where the headset straps were situated. It is thus reasonable to assume that the ERPs at POz' were compromised by the constant mechanical pressure of the VR headset, making it difficult to detect reliable peak onset latencies.



FIGURE 6 Power Spectral Densities (PSDs) extracted from EEGLAB for each of the midline channels are depicted relative to the 'Task' condition. All the spectra were divided into five bands (theta: 4-8 Hz; lower alpha: 8-10 Hz, upper alpha: 10-12 Hz; beta: 12-30 Hz; gamma: 30-40 Hz), independently analyzed through five 2x2x2x2x6 repeated measures ANOVAs. The shaded area around the means represents the confidence interval (CI) of 0.95. Bands highlighted in grey gave yielded significant effects and are complemented by stars indicating the significance level of the statistical test (* $p \le .05$; ** $p \le .01$; *** $p \le .001$)

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Finally, the same Simon effect (Simon, 1969) found in reaction times and response accuracy was observed for the P3 component as well. A smaller P3 amplitude was observed for incongruent hand-hemifield responses (Blue Left and Yellow Right) in contrast to congruent responses (Blue Right and Yellow Left). These results have repeatedly been observed in previous static setups (Melara, Wang, Vu, & Proctor, 2008; Ragot & Renault, 1981; Zhou, Zhang, Tan, & Han, 2004) and are here replicated for a naturalistic walking task. Interestingly, as shown by the three-way interaction between 'Task', 'Target', and 'Hemifield', the incongruence of hand-hemifield response did not affect P3 amplitude within the Single-task but only within the Dual-task condition. These results indicate a greater difficulty and resource conflict for the Dual-task walking condition when participants needed to respond to targets with an incongruent hand-hemifield assignment. Due to increased resources necessary for walking, the additional button press response created stronger interference compared to the standing condition (Ruffieux, Keller, Lauber, & Taube, 2015). Such a resource conflict is reduced for the Single-task in which the Simon effect was thus marginalized. While the Simon effect in our setup is noteworthy, the more important finding is the observed impact of the hand-hemifield incongruence on brain dynamics only during natural overground walking but not while standing.

4.3.1 **Power spectral densities**

Gradually proceeding from lower to higher frequency bands (Figure 6), the present study replicated an inverse modulation of theta and alpha activity related to the task demand. An increased theta power in the Dual- as compared to the Singletask was observed over frontal and centro-parietal areas spreading out to occipital sites. Moreover, a decreased alpha power has been observed as well, which was prominent from central sites up to parieto-occipital regions for lower alpha frequencies, and from frontal up to parietal regions for the upper alpha frequency range. These modulations have previously been observed when contrasting walking with a static condition (Pizzamiglio et al., 2017; Presacco et al., 2011; Seeber et al., 2014) and also with a dual-task walking (Pizzamiglio et al., 2017; Beurskens et al., 2016). Particularly, Beurskens et al. (2016) demonstrated lower alpha over frontal and occipital areas when walking and performing both cognitive and motor tasks as a function of cognitive load. In contrast, the observed alpha decrease in our data was not limited to frontal and central sites, but was observed over widespread regions from frontal to parieto-occipital midline channels. Overall, in the present study, theta and alpha modulations were replicated during walking overground in a virtual scenario, providing evidence for higher demand during dual-task walking.

Moving toward higher frequencies, we further observed a decrease in beta power over centro-parietal leads under

dual-task walking, which turned into a beta power increase from parietal to occipital leads. Furthermore, a strong increase in gamma activity for all midline electrodes when walking was also observed, which became increasingly pronounced from frontal to occipital sites. The observed centro-parietal decrease is in line with the beta suppression that was reported to be related to motor activation induced by walking (Engel & Fries, 2010; Pizzamiglio et al., 2017; Seeber et al., 2014; Wagner et al., 2014). However, our data show higher beta activation from parietal to occipital sites under dual-task walking. This result is in line with previous studies contrasting standing and walking conditions (Presacco et al., 2011) and with studies interpreting this trend as due to higher demand in the motor (Beurskens et al., 2016) or cognitive domain (Pizzamiglio et al., 2017). Similarly, gamma frequencies have previously been shown to be related to body instability, which can occur in dynamic situations like walking (Slobounov et al., 2009) but also while walking and performing an additional cognitive task (Marcar et al., 2014). Both factors were involved in the present study replicating previous results and pointing to a role of gamma activity in the stabilization of posture as well as additional tasks during walking. However, given the contradictory observations of beta modulation in mobile contexts and considering that a walking phase without additional cognitive tasks was not included in our experimental design, a functional role of both beta and gamma in CMI during overground walking cannot be derived from our results. In addition, interpretations of gamma activity have to consider a potential confound due to neck muscle activity, which is likely to contaminate the surface EEG signal when walking (Goncharova, McFarland, Vaughan, & Wolpaw, 2003). In the present experiment, we minimized head movements by requiring participants to keep their head aligned with the virtual sphere in front of them. However, it is important to point out that neck muscles activity was not recorded in the present study with participants walking overground without physical constraints. As a solution to this issue, the integration of electromyographic recordings from the neck might significantly improve the ICA decomposition for recordings involving neck muscles activity like walking (Richer, Downey, Nordin, Hairston, & Ferris, 2019). Future studies might consider the additional recording of electromyographic signals from the neck for investigating CMI effects including different conditions of motor and cognitive tasks and how these impact beta and gamma activity.

4.3.2 **Principal contributions**, limitations, and future directions

Within the present virtual framework, the main question was whether measuring human brain dynamics during standing and overground walking can provide further insights into the human brain dynamics accompanying CMI in an ecologically valid setup. We addressed this question by adding a visual cognitive task to an overground walking and compared this to the same task dynamics during simple standing to investigate how visual attention is directed while visual resources are necessary to plan and control future walking behavior. As an option for studying neural mechanisms underlying visual CMI during overground walking, a VR system was incorporated in a MoBI setup, taking a step toward the investigation of more natural and active behaviors involving visual processing. In this context, the perceived mental load during the Single- and the Dual-task did not differ, and neither did the performance. From a neural perspective, instead, our results demonstrated that simply walking overground at a natural speed already interferes with the execution of a low-demanding cognitive task in the visual domain. This was revealed by a P3 amplitude reduction when executing the cognitive task in motion as compared to standing and was also reflected in the frequency domain with increasing theta and decreasing alpha power over widespread regions of the brain. Even though important modulations at higher frequencies were also observed (beta and gamma frequencies), whether and how those are related to cognitive and/or motor load needs to be further investigated.

Thus, on the same interpretative line of previous works on mobile cognition, our results reflect CMI to take place during Dual-task walking even when involving only a low-effort visual discrimination task. As an addition to previous works, it was also demonstrated that the above-mentioned neural markers can be used to identify changes in attention during active behaviors involving visual processing in VR and overground walking. However, the visual discrimination task used in the present study was particularly easy for the young population. Future investigations implementing an improved virtual design with more challenging cognitive and motor tasks will have to investigate the roles of both cognition and motion in brain dynamic modulations, still controlling relevant experimental features in an ecologically valid way. We are confident that the implementation of head-mounted VR systems in dual-task scenarios will provide an important contribution to better understand 'natural cognition', representing the step from the laboratory setting to the real world.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTIONS

KG, CTD, and FN were responsible for the early study concept and design. CTD and FN collaborated for programming the virtual environment in Unity. FN was responsible for participant recruitment and data collection. JP, KG, and FN contributed to the preprocessing and analysis of EEG data, and all authors contributed to data interpretation. FN initially drafted the manuscript and KG, CTD, and JP subsequently provided extensive critical revisions. The final version of the publication was approved by all authors.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

Upon acceptance of the article, data and code will be made available on an open-source repository.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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