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Additive Effects of Cognitive Load, Motor Demand, and Environmental Complexity on Attention: A Real-World EEG-study

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Abstract

The capacity to regulate one's attention in accordance with fluctuating task demands and environmental contexts is an essential feature of adaptive behavior. Although the electrophysiological correlates of attentional processing have been extensively studied in the laboratory, relatively little is known about the way they unfold under more variable, ecologically-valid conditions. Accordingly, this study employed a 'real-world' EEG design to investigate how attentional processing varies under increasing levels of cognitive, motor, and environmental demand. Forty-four participants were exposed to an auditory oddball task while (1) sitting in a quiet room inside the lab, (2) walking around a sports field, and (3) wayfinding across a university campus. In each condition, participants were instructed to either attend to (i.e., count) or ignore oddball stimuli. While behavioral performance was similar across the lab and field conditions, oddball count accuracy was significantly reduced in the campus condition. Moreover, event-related potential components (mismatch negativity and P3) elicited in both 'real-world' settings differed significantly from those obtained under laboratory conditions. These findings demonstrate the impact of environmental factors on attentional processing during simultaneously-performed motor and cognitive tasks, highlighting the value of incorporating dynamic and unpredictable contexts within naturalistic designs.

Keywords: Mobile EEG, ERP, attention, real-world, cognitive load

Introduction

Attention is a finite resource that must be strategically managed throughout daily life. The hyper-connected nature of the modern world, and in particular, the ubiquitous devices, apps, and media that constantly vie for our attention, exposes us to an abundance of information that must be selectively sampled, navigated, and at times, held in abeyance. Arguably, it has never been more important to understand the impact of competing attentional demands on cognitive function and motor action. Therefore, the present study taps into this field that, while still in its infancy, is attracting increasing interest, by investigating psychophysiological effects of cognitive task load, motor demands, and environmental complexity on attention in real-world scenarios.

A great deal of knowledge about the nature of attention as well as the influence of distracting stimuli has been derived from carefully controlled laboratory studies (e.g., Schröger & Wolff, 1998). By contrast, much less is known about the characteristics of attention under real-world situations. However, recent technological developments in electroencephalography (EEG) and eye-tracking have enabled researchers to address such topics from a neurophysiological perspective outside the laboratory (e.g., while driving). The present study exploits this technical progress to examine how event-related potentials (ERPs) relating to sensory and attentional processing differ across laboratory and more ecologically-valid situations. Here, we focus on the P3 component, which has been most frequently investigated in previous real-world studies (e.g., Reiser et al., 2019), and the mismatch negativity (MMN), which constitutes an index of early sensory processing.

The P3 constitutes the third positive deflection after stimulus presentation, typically occurring at a latency ranging 250—500 ms and most dominantly in centro-parietal areas [3,4]. This component has been related to updating and categorization processes [5], the intensity of performance [6,7], as well as the amount of resources dedicated to task performance [8,9]. Furthermore, the P3 can serve as an index of the distribution of attention in competing concurrent tasks [10] and has been shown to be sensitive to alterations in task difficulty [11].

The MMN is elicited in the presence of any discriminable change in some repetitive aspect of stimulation. Peaking within 100–250 ms from change onset, the MMN exhibits the strongest intensity in temporal and frontal areas of topographic scalp maps, and can be detected even when the participant pays no attention to the task [12–14]. Furthermore, some argue that the MMN

is most dominant when participants direct their attention away from the stimulus stream [15]. Although the MMN has been most intensively studied in the auditory modality [16], previous studies identified the component also in visual settings [17].

Initial studies investigating the influence of motor demands (e.g., varying gait parameters) on ERPs mainly used simple cognitive tasks performed while walking on a treadmill. These studies suggest that the amplitude, latency and topography of event-related potentials (N1, N2, P3) vary depending on the difficulty of both the motor and the cognitive task [18,19]. When occurring in parallel with a cognitive task, motor demands (e.g., during walking) can thus be viewed as inducing a dual-task setting that calls for appropriate allocation of attention between cognitive and motor systems [20].

More recent studies have applied EEG in increasingly realistic conditions [2]. These studies demonstrate a relation between attentional processing and the cognitive load induced by each situation. For example, by identifying a decreased cognitive task performance, parietal P3 amplitude, and frontal midline theta power with increased situational load (standing vs. walking on a treadmill vs. walking along a hallway) [21]. Furthermore, these findings show a greater impact of environmental factors on electrophysiological markers of attention compared to motor demands (being wheeled along a hallway vs. walking on a treadmill). To date, however, most real-world studies involve fairly undemanding environmental settings, such as an empty straight corridor [21] or the lawn of an institute's grounds [2].

Within a more naturalistic context, Aspinall and Colleagues described EEG changes in terms of increased engagement and arousal in more busy environmental settings (urban shopping street and busy commercial district) compared to green spaces [22]. However, the interpretation of these findings is complicated by the authors' reliance on proprietary EEG metrics that are not commonly reported in the literature. More recently, Pizzamiglio and Colleagues reported increased theta and beta power when participants were walking across campus while conversing, as compared to standing [23]. However, studies that have analyzed attention-related ERP responses under such ecologically valid conditions are rare and limited to virtual reality [20].

In sum, previous real-world studies have either focused on the effect of motor demands [2], used relatively simple scenarios with limited stimuli [21], or did not analyze attention-related

ERPs [23–25]. Here, we sought to fill an important gap in this literature by investigating the additive effects of motor demands, environmental complexity, and cognitive task load on such ERPs. We report findings from an auditory oddball paradigm in which participants either attended to or ignored experimental stimuli while engaged in three situational contexts: (1) ordinary laboratory conditions, (2) walking around a sports field, and (3) navigating a university campus. Behavioral data and ERPs pertaining to the MMN and P3 were analyzed to investigate the effect of each experimental manipulation on task performance and attentional processing.

Methods

Participants

Healthy, right-handed, native English-speaking adults aged 18-40 years were eligible to participate in this study. Of the 44 recruited participants, one was excluded due to left-handedness, and a further two were excluded due to missing EEG data. The remaining sample consisted of 26 females and 15 males aged 18–39 years (mean = 23.1 years, SD = 4.8). All participants reported normal (or corrected-to-normal) vision and audition, no history of neurological or psychological disorders, and no diagnosed intellectual or language disorder.

The study was performed in accordance with the ethical standards laid down in the Declaration of Helsinki and approved by the local ethics committee at the University of South Australia (ID: 0000034991). All participants provided written informed consent prior to the experiment and were informed that they could end participation at any time without reprisal.

Materials

The auditory oddball task comprised two distinct tones, one presented frequently (standard) and the other infrequently (deviant). These stimuli were a French horn tone (Dominant frequency of 1046.502Hz, High C or C6) and a piano tone (Dominant frequency of 523.251Hz, Middle C or C5). We used complex tones because they constitute more naturalistic stimuli than pure tones [26].

Tones were presented binaurally via conventional in-ear headphones for 150 ms, with an interstimulus interval of 350 ms. One-hundred and fifty stimuli were presented per block, of which 13-30% were deviants (mean = 20%). Tones were randomly assigned as the standard/deviant for each environment. Stimulus presentation was driven by OpenSesame v3.0.7 [27] running on a commercial compact laptop in conjunction with BrainVision StimTrak (Gain = 10, Trigger Level = 1V).

Procedure

After providing written, informed consent, participants completed a demographic questionnaire and the Edinburgh Handedness Inventory [28], followed by the EEG setup. Before starting the task, the two tones were presented to familiarize participants with the stimuli. Participants performed 5 blocks of the oddball task in each of the three environments (Lab, Field, Campus) while counting the number of deviant stimuli (Count), and again in each of the three environments while ignoring task stimuli (Ignore). The order of the task manipulation was randomized, as was the order of environmental conditions nested within either task condition. We chose counting rather than button press responses as our measure of attentional engagement because previous studies have reported that P3 topography is confounded by motor-evoked potentials [29].

Within the Lab condition, participants performed the oddball task while sitting alone in an interview room. The room was sparsely furnished with a large table, six chairs and a sideboard, surrounded by three white walls without pictures, and one frosted glass wall. Participants sat on a chair with armrests, with the laptop in front of them (supported by a harness strapped to their torso). The participant's gaze was directed towards a white wall. The glass wall, which separated the interview room from a corridor, was on their right.

The Field condition involved walking around a grass sports field at the Magill campus of the University of South Australia, Adelaide. The sports field is surrounded by a grandstand, a car park for members of the university, trees and fencing (see Figure 1a). The Campus condition involved navigating a pre-defined route through the university campus adjacent to the sports field. Participants were provided a map with a cross-marked destination (red point) to which they should navigate via several waypoints (yellow points) (see Figure 1b). The route included both outdoor and indoor sections. Participants had to use stairs, open doors, and interact with other people on the campus.

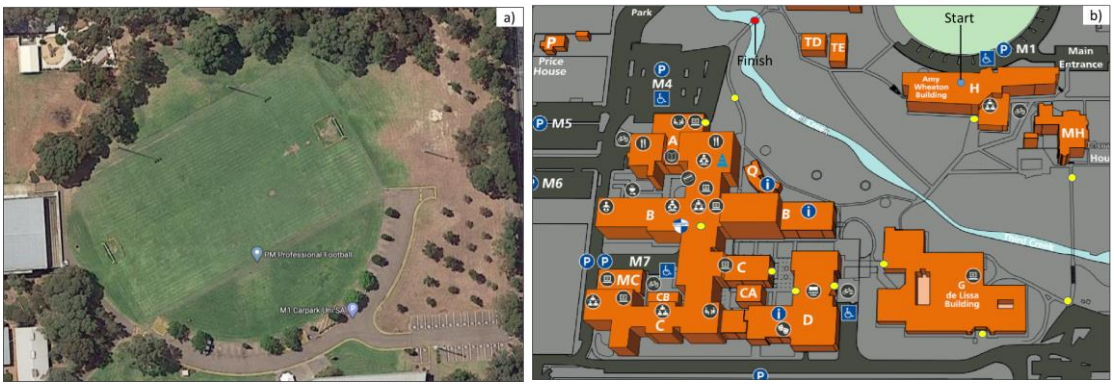

Figure 1 a) Grass sports field at the Magill campus at the University of South Australia (from *Google Maps*, by Google, https://bit.ly/2R0XXjl), b) Reproduction of the map provided to the participants in the "campus condition", showing the route across the Magill campus. Participants started at the blue dot and had to pass the yellow dots on their way to the red dot that represents the finish.

During both walking conditions, participants carried the laptop in front of them (supported by the harness) while carrying the StimTrak in a plastic pocket (attached with a lanyard) over one shoulder as they made their way along the route. The entire testing session lasted between 2.5 and 3 hours, with sufficient breaks between conditions to avoid fatigue.

EEG acquisition and preprocessing

The EEG was continuously recorded from 32 Ag/AgCl actiCAP mounted active electrodes using a Brain Vision LiveAmp 32 amplifier (Brain Products GmbH, Gilching, Germany). Electrode positions conformed to the extended 10–20 system. All channels were digitized at a sampling rate of 500 Hz. AFz served as the ground and FCz as the online reference. Electrode impedances were below 20 kΩ at the beginning of the experiment. EEG data were stored on a micro SD card inside the amplifier; the amplifier was kept inside a mesh pocket on the back of the EEG cap during the experiment. After the experiment, the data were transferred from the SD card to a hard drive for offline processing and analysis.

EEG data were preprocessed in MATLAB R2019b (v9.7.0.1319299; The MathWorks, Natick, MA) using custom-built scripts incorporating functions from the EEGLAB (v2019.1;[30]) and ERPLAB (v8.02;[31]) toolboxes. Marker files were first manually edited to remove artefactual triggers caused by feedback from the auditory equipment. Edited data were then imported into EEGLAB and downsampled to 250 Hz. Accelerometer channels and non-experimental recording segments were excluded. The online reference was then reintroduced into the dataset, and the data re-referenced to the average of TP9 and TP10 in order to approximate linked mastoids. The data were then high-pass filtered (passband edge = 0.5 Hz, transition width = 0.5

Hz) using a zero-phase, hamming-windowed, finite impulse response (FIR) sinc filter (implemented in the *pop_eegfiltnew* function from the firfilt plugin; v2.4).

Filtered data were processed with artifact subspace reconstruction (implemented with the *pop_clean_artifacts* function from the clean_rawdata plugin; v2.3). This routine was used to remove flat or noisy channels (flatline criterion = 5 s; channel correlation criterion = 0.80; line noise criterion = 4), and to correct for large amplitude artifacts (burst criterion = 10, [32,33]). The data were then decomposed into independent components (*binica* implementation of the extended logistic infomax ICA algorithm,[34,35]), which were automatically classified using the ICLabel plugin (v1.3, [36]). Components classed as ocular in origin with >90% probability were subtracted (median = 2, range = 0-3).

Missing channels (median = 1, range = 0-4) were interpolated for the purposes of ERP visualization but excluded from statistical analysis. All EEG event markers were systematically shifted -200 ms relative to their recorded latencies (*pop_erplabShiftEventCodes*) to account for the lag in signal transmission introduced by the StimTrak. The EEG was then epoched [-200, 800 ms] relative to the corrected event markers. Extracted epochs were mean-centered and subjected to a moving window artefact rejection routine (*pop_artmwppth*; voltage threshold = 150 µV, time period = [-200, 600 ms]; window size = 100 ms, window step = 50 ms). Mean voltages were then extracted from three time-windows per epoch (Prestimulus = [-200, 0 ms]; MMN = [100, 250 ms]; P3 = [250, 500 ms]) and exported for statistical analysis. ERPs were low-pass FIR filtered (20 Hz passband edge, 5 Hz transition width) prior to visualization.

Data analysis

All statistical analysis was conducted in *R* (v3.6.2; R Core Team, 2019) using the *RStudio Desktop IDE* (v1.2.5033; R Studio Team, 2015). Behavioral and EEG data were analyzed using linear mixed-effects models fit using the *lmer()* function from *lme4* (v1.1-23; Bates et al., 2015). All models included a by-participant random intercept term to account for non-independence of (within-subject) observations. All categorical independent variables were entered as unordered factors using sum-to-zero contrast coding (reference category coded -1).

For the behavioral model, deviant counts for each block of the Count task were included as the dependent variable, while number of deviant stimuli and environmental condition were included as independent variables. Note that including the number of presented deviants as a

covariate controlled for differences in the ground truth count across blocks, enabling us to implicitly model count accuracy as a function of environmental condition.

Separate EEG models were fitted for the MMN and P3 time-windows, with single-trial mean voltage estimates serving as the dependent variable. Environmental condition, stimulus type, and task manipulation were entered as independent variables and permitted to interact with one another. Models additionally included mean prestimulus voltage as a scaled covariate in order to address trial-by-trial variation in prestimulus activity [40], and by-channel random intercepts to account for topographic differences in voltage estimates. Random slopes were included on participant intercepts for stimulus, environment, and task factors in the MMN model, and for environment only in the P3 model (more complex random effects structures failed to converge).

Main effects and interaction terms were assessed using Wald tests from Type-II ANOVA tables obtained from the *car* package (v3.0-10; Fox & Weisberg, 2018a). Model summary tables were produced using *sjPlot* (v2.8.7; Lüdecke, 2020). P-values for model terms were derived using Satterthwaite's method for approximating degrees of freedom. Post-hoc contrasts (with Tukey correction for multiple comparisons) were obtained via the *emmeans* package (v1.5.1, [43]). Plotted model predictions are estimated marginal means (also obtained from the *emmeans* package) and visualised with the aid of *tidyverse* (v1.3.0, [44]). Model predictions are plotted with 84% confidence intervals, where non-overlapping intervals indicate a significant difference at $\alpha = .05$ [45].

Data Availability Statement

Raw and preprocessed datasets, along with all code necessary to reproduce the analysis pipeline reported in this paper, are openly available from the OpenNeuro database [Dataset: doi: 10.18112/openneuro.ds003620.v1.0.0]. Data were archived in accordance with the Brain Imaging Data Structure (BIDS) standard for EEG [46] with the assistance of functions from the bids-matlab-tools plugin (v5.2, https://github.com/sccn/bids-matlab-tools).

Results

Behavioral data

Two participants were excluded from analysis due to numerous highly inaccurate count estimates (more than double the number of presented deviants on the majority of blocks). Due to a programming error, count estimates from the final block of trials were missing for 21 participants. A further 16 count estimates were excluded as outliers (> 3 *SD* from the sample mean after estimates had been normalized by the number of presented deviants).

Numerically, mean count estimates were similar across Lab and Field conditions, but reduced in the Campus condition. Linear mixed-effects modelling revealed a significant effect of Environment ($\chi^2(2)=12.08$, $p=.002$) after controlling for the number of presented deviants. Post-hoc contrasts revealed that count estimates were significantly reduced during the Campus condition compared to both the Lab ($p=.005$) and Field ($p=.014$) conditions. No significant difference was found between Lab and Field conditions ($p=.930$).

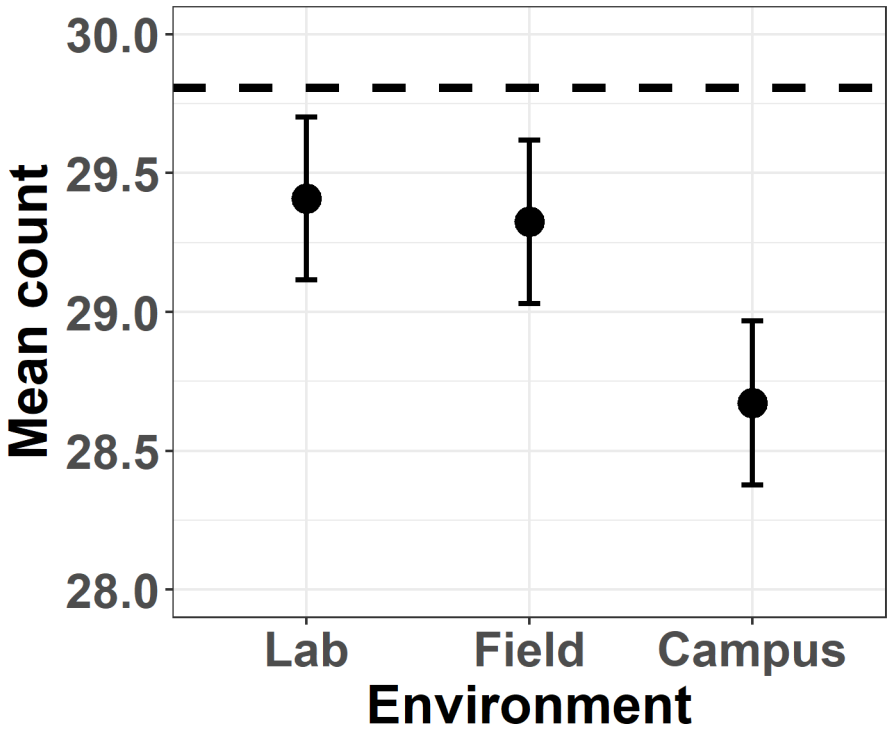

Figure 2. Estimated marginal mean deviant counts per block across environmental conditions. Error bars indicate 84% confidence intervals. Dashed line indicates perfect performance.

Event related potentials

A further five participants were excluded from the ERP analysis due to excessively noisy recordings (>50% epochs rejected due to artifact).

Grand average ERPs and difference waveforms from electrodes Fz and Cz are displayed in Figure 3 (see supplementary materials for additional ERP plots). In the Lab condition, both channels revealed a marked negative-going waveform in the early time-window for deviant stimuli, consistent with a MMN component. This effect was evident irrespective of task manipulation, although scalp topographies displaying the mean voltage difference between stimuli indicate that the effect was more pronounced over centro-parietal sensors during the Count task (see Figure 3). Conversely, deviants elicited a strong positive deflection in the first half of the later time-window, consistent with a P3 response. This effect was also strongest over centro-parietal channels in the Count task.

Field and Campus conditions rendered qualitatively similar ERP waveforms. Deflections in the MMN time-window were positive-going for standard tones, and negative-going for deviants, rendering a negative difference wave that was most pronounced over central electrode sites. This pattern of activity was again reversed in the P3 time-window, resulting in a centrally distributed positivity that peaked approximately 300 ms post stimulus onset. This effect was less pronounced in the Campus compared to the Field condition. Comparing across task manipulations, the difference between deviant and standard waveforms in the MMN time-window was slightly accentuated, and more centrally distributed, in the Ignore task, while the P3 window revealed slight accentuation over centro-parietal regions in the Count task. Taken together, the qualitative pattern of both the early and late ERP components elicited during the walking conditions was generally similar to those elicited in the Lab condition, but of reduced magnitude.

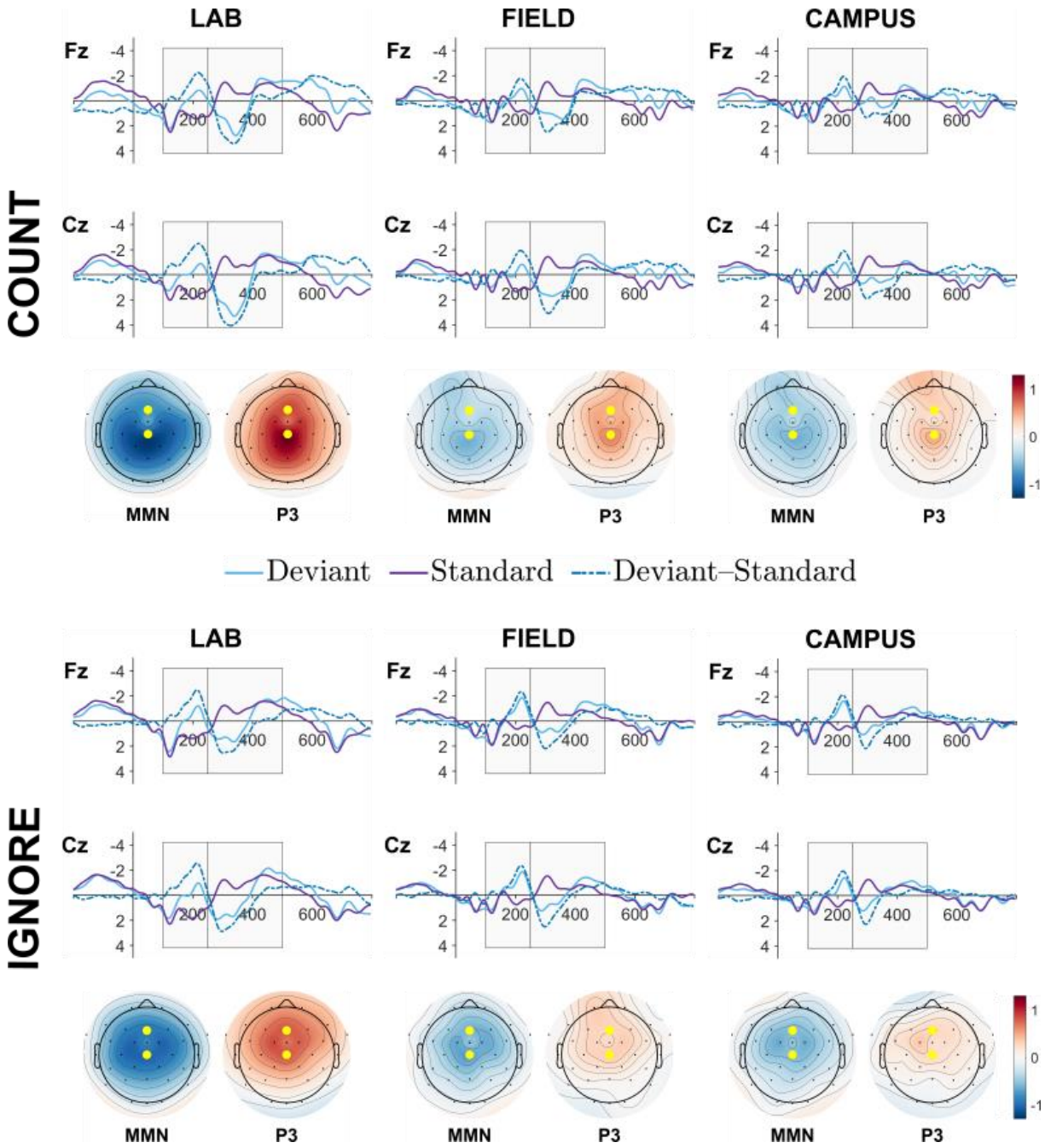

Figure 3. Grand average ERPs (solid lines) and difference waveforms (broken lines) for electrodes Fz and Cz. Plots factorized by environment (columns) and task (top and bottom panels). Light blue waveforms depict ERPs evoked by deviant stimuli, purple waveforms depict ERPs evoked by standard stimuli. Broken lines indicate the difference in mean voltage between deviants and standards. Topographies depict mean voltage differences averaged across the two time-windows of interest (100 – 250 ms; 250 – 500 ms). Yellow dots indicate electrode locations for plotted ERPs (upper = Fz, lower = Cz).

MMN time-window

The linear mixed-effects model for the MMN time-window is summarized in Table 1. Type II Wald tests revealed a significant three-way interaction between stimulus, task, and environment (χ^2 (2) = 14.83, p < .001). This interaction is resolved in Figure 4. This plot reveals that mean voltage was significantly more negative for deviants vs. standards across all conditions (ps<.032). In line with the ERP waveforms characterized above, the magnitude of this difference was greatest in the Lab condition, and reduced in the other two conditions. This effect was driven by the modulation of cortical responses to standard stimuli, which were less positive-going in both conditions outside the lab.

The difference between stimulus responses across environmental conditions was broadly similar irrespective of whether participants counted or ignored task stimuli. Nonetheless, counting accentuated the difference between standard and deviant responses in the Lab condition relative to the Field condition (p=.002). In contrast, the difference between stimulus responses across Field and Campus conditions did not significantly vary as a function of cognitive task (p=.771).

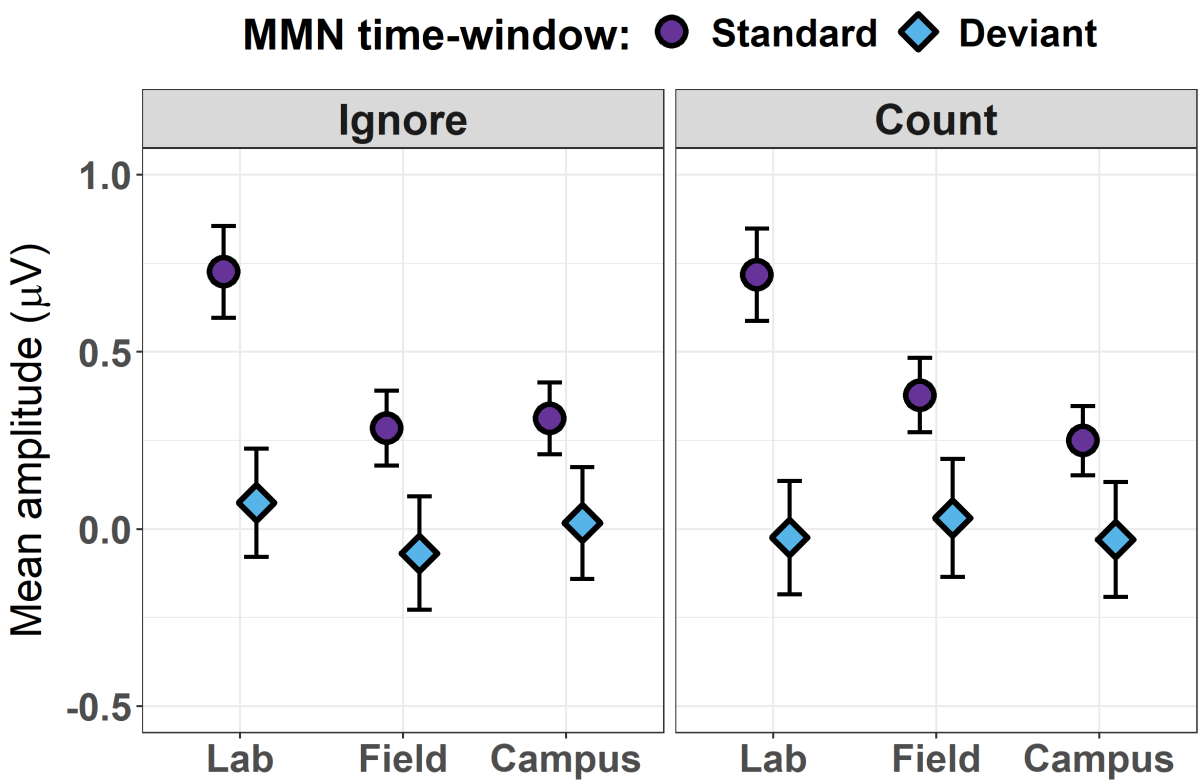

Figure 4. Estimated marginal mean voltages for the MMN time-window factorized by stimulus, task, and environment. Error bars indicate 84% confidence intervals.

Table 1. *Summary of MMN and P3 linear mixed-effects models.*

	MMN time-window				**P3 time-window**			
Predictors	*Estimates*	*S.E.*	*t-stat*	*p-value*	*Estimates*	*S.E.*	*t-stat*	*p-value*
(Intercept)	0.22	0.08	2.82	**.007**	-0.15	0.07	-2.16	**.035**
stimulus[S.Standard]	0.22	0.04	5.51	**<.001**	-0.18	0.00	-74.46	**<.001**
task[S.Ignore]	0.00	0.02	0.13	.900	-0.03	0.00	-14.05	**<.001**
environ[S.Lab]	0.15	0.05	2.99	**.005**	-0.03	0.04	-0.59	.561
environ[S.Field]	-0.07	0.03	-2.27	**.030**	0.01	0.03	0.48	.636
prestim.s	-1.11	0.00	-445.04	**<.001**	-1.40	0.00	-743.81	**<.001**
stimulus[S.Standard] : task[S.Ignore]	-0.01	0.00	-1.79	.073	0.04	0.00	16.63	**<.001**
stimulus[S.Standard] : environ[S.Lab]	0.13	0.00	28.74	**<.001**	-0.14	0.00	-42.65	**<.001**
stimulus[S.Standard] : environ[S.Field]	-0.05	0.00	-10.64	**<.001**	0.05	0.00	14.72	**<.001**
task[S.Ignore] : environ[S.Lab]	0.02	0.00	5.60	**<.001**	-0.06	0.00	-17.89	**<.001**
task[S.Ignore] : environ[S.Field]	-0.05	0.00	-11.24	**<.001**	-0.01	0.00	-3.14	**.002**
stimulus[S.Standard] : task[S.Ignore] : environ[S.Lab]	-0.02	0.00	-3.84	**<.001**	0.02	0.00	5.32	**<.001**
stimulus[S.Standard] : task[S.Ignore] : environ[S.Field]	0.01	0.00	1.63	.102	0.01	0.00	2.46	**0.014**
Random Effects								
σ^2	24.72				14.03			
τ_{00}	0.16 $_{\text{subject_id}}$				0.12 $_{\text{subject_id}}$			
	0.04 $_{\text{channel_id}}$				0.05 $_{\text{channel_id}}$			
τ_{11}	0.05 $_{\text{subject_id.stimulus[S.Standard]}}$				0.06 $_{\text{subject_id.environ[S.Lab]}}$			
	0.09 $_{\text{subject_id.environ[S.Lab]}}$				0.02 $_{\text{subject_id.environ[S.Field]}}$			
	0.03 $_{\text{subject_id.environ[S.Field]}}$							
	0.01 $_{\text{subject_id.task[S.Ignore]}}$							
ρ_{01}	-0.57 $_{\text{subject_id.stimulus[S.Standard]}}$				0.29 $_{\text{subject_id.environ[S.Lab]}}$			
	-0.03 $_{\text{subject_id.environ[S.Lab]}}$				-0.13 $_{\text{subject_id.environ[S.Field]}}$			

	0.15 $_{\text{subject_id.environ[S.Field]}}$	
	-0.10 $_{\text{subject_id.task[S.Ignore]}}$	
N	34 $_{\text{subject_id}}$	34 $_{\text{subject_id}}$
	31 $_{\text{channel_id}}$	31 $_{\text{channel_id}}$
Observations	3972998	3972998

P3 time-window

The linear mixed-effects model for the P3 time-window is summarized in Table 1. Again, the three-way interaction involving stimulus, task, and environment was significant (χ^2 (2) = 62.15, p < .001). This interaction is resolved in Figure 5.

Pairwise comparisons of responses to standards vs. deviants were again significant across all conditions (*p*s <.001). The difference between these responses was greater in the Lab condition vs. the Field condition, irrespective of whether participants were actively attending to the stimuli or not (*p*s <.001). However, the difference in stimulus responses across Field and Campus conditions was significantly modulated by task manipulation, with counting serving to increase the difference between stimulus responses in the Field condition (p <.001).

In contrast to our analysis of the MMN time-window, differences between the Count and Ignore conditions in the P3 time-window were primarily driven by modulations of deviant tone processing. Deviant stimuli elicited significantly stronger positivities in both the Lab and Field conditions when being counted as opposed to ignored (*p*s <.001). A similar, albeit non-significant, trend was noted in the Campus condition (p = .077).

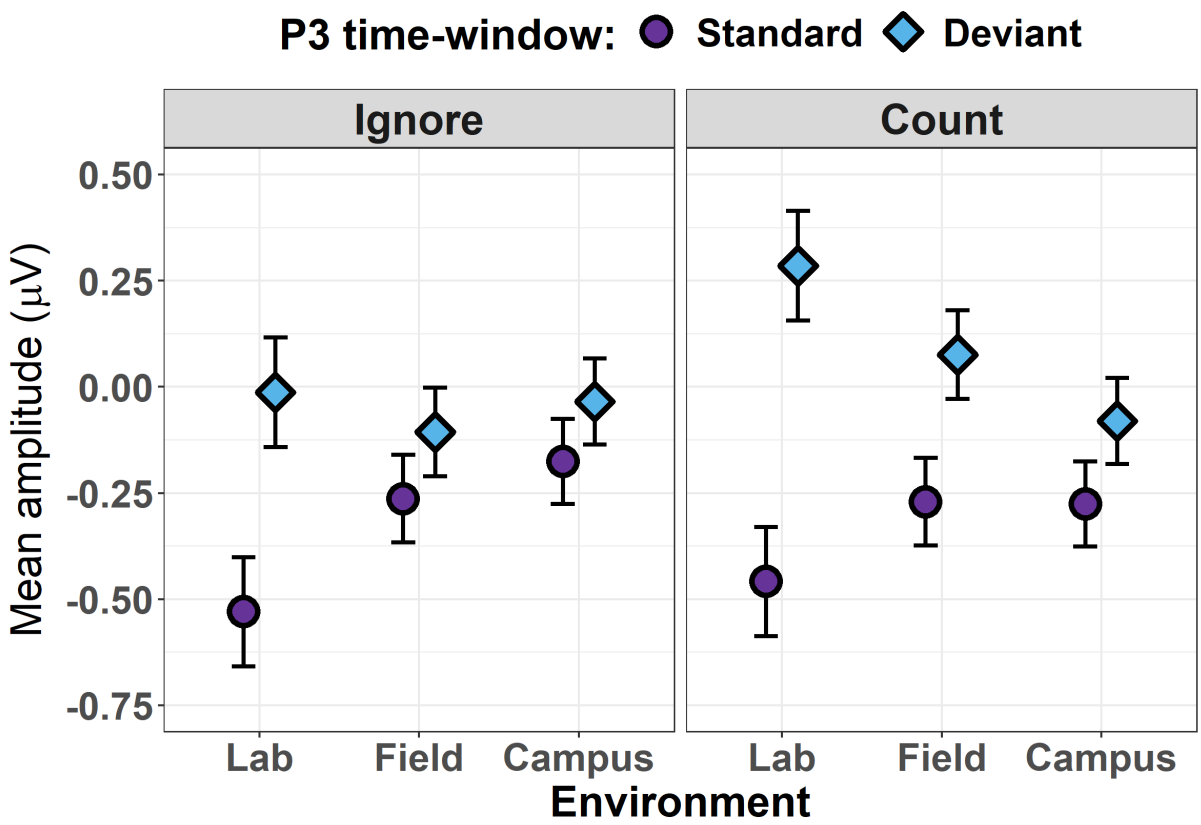

Figure 5. Estimated marginal mean voltages for the P3 time-window factorized by stimulus, task, and environment. Error bars indicate 84% confidence intervals.

Discussion

To what extent is attentional processing affected by the situational context and its associated demands? The present study addressed this question by comparing electrophysiological correlates of attentional processing between a traditional lab-based setting and two more naturalistic, dynamic scenarios. The manipulation of task instruction (i.e., to count or ignore oddball stimuli) across these three conditions enabled us to further compare the interaction of different levels of motor and environmental demands on top-down attentional engagement with task stimuli.

While participants were generally able to perform the oddball counting task with a high degree of accuracy across all three environmental conditions, linear mixed-effects regression analysis revealed that oddball counts were significantly less accurate in the Campus condition. This suggests the additional complexity entailed by this condition – both in terms of the more variable and unpredictable sensory stimuli it availed, and the more varied patterns of motor activity it solicited – were sufficiently distracting to degrade attentional focus on this simple cognitive task. By contrast, the additional motor demands and sensory complexity induced by walking around a sports field did not significantly affect task performance compared to sitting in a quiet room.

By contrast, the main findings from our ERP analyses revealed substantial differences in both the MMN and P3 components under 'real-world' versus laboratory conditions. This finding suggests that more ecologically-valid conditions involving motor co-ordination may modulate attentional processing despite ostensibly good behavioral task performance. Compared to walking around the sports field, wayfinding across campus resulted in rather more subtle differences, perhaps surprisingly so given the superior behavioral performance and relative simplicity of the Field condition. Differences between these conditions were limited to the Count task, and were more pronounced for the P3 response than the MMN.

With respect to previous studies of MMN and P3 components, findings from our Lab condition confirm the validity of the present results [15,16,47]. Specifically, the pre-dominant distribution of activity across fronto-central and centro-parietal regions of the scalp, respectively, was in accordance with findings from dual-task walking studies [48,49], as well as basic studies of the MMN [12,50] and P3 [51].

Increasing evidence from previous laboratory as well as real-world studies point to the fact that attention on a given task depends on aspects such as task-difficulty, concurrent motor demands, as well as environmental conditions [21]. However, especially in real-world scenarios findings are rare and partly controversial. The present findings tap into this gap – for example – by identifying distinctions in the effects of different real-world scenarios on attentional resources allocated to cognitive task-performance, by varying cognitive task difficulty. In contrast, previous studies with similar cognitive tasks reported no differences in P3 amplitude between different real-world scenarios [2]. This apparent discrepancy can be explained by the varied characteristics of the real-world scenarios included within these studies. While simple conditions are comparable to the present sports field condition (e.g., walking on a circuit on the lawn in front of the university), more complex scenarios differ significantly from walking across the campus (e.g., obstacle course on an empty area or corridor).

Together with previous findings, we suggest that commonly-encountered everyday situations (e.g., wayfinding, interacting with other people, etc.) may place attentional resources under higher demand than physically-demanding situations (e.g., obstacle course) within a controlled, unchanging environment. In accordance with previous real-world EEG findings [21], evidence from laboratory studies, which used similar cognitive tasks, also identified no significant effects of increased motor demands (e.g., slow walking vs. fast walking on a treadmill) [18]. However, studies with more difficult cognitive tasks (higher number of target-stimuli and increased complexity) report differences in amplitude, latency and topography of ERP components with increasing motor demands [19]. It follows that the amount of attention deployed during a given cognitive task is influenced by the complexity of real-world situations, but more importantly, that the influence of environmental complexity is also modulated by cognitive task difficulty.

In contrast to previous studies, the present findings revealed significant interactions between stimulus, task, and condition for both ERP time-windows [2]. The difference between standard and deviant stimulus responses diminished from lab to ‘real-world’ conditions. For the MMN, this effect was predominantly driven by a reduction in the positivity evoked by standard stimuli while walking; deviants, by contrast, evoked similar voltage levels irrespective of environmental or task condition. Analogously, standard stimuli evoked less-negative potentials in the P3 time-window during the walking conditions compared to the lab.

This pattern of results is broadly consistent with a predictive coding-style account of perceptual learning [52,53] and its attentional modulation via the mechanism of synaptic gain-control [54,55]. Under the assumption that frequent, regular presentations of the standard tone enable the brain to construct a precise model of stimulus features (e.g., pitch, duration), the sensory signals generated by the repeated stimuli are efficiently cancelled-out (or 'silenced') by descending model predictions [14,56]. The present findings suggest this ability may be reduced when moving through (and actively engaging with) more complex, dynamic environments. A possible explanation for this is that the additional, competing demands imposed on attention by more naturalistic scenarios may limit the brain's capacity to accurately and precisely model recurrent stimuli, such that they are subject to more elaborate cortical processing than they would ordinarily be afforded under laboratory conditions. The functional upshot of this account is that standard stimuli may essentially be treated more like deviants when occasioned in the context of more complex, variable, and uncertain conditions than those typically encountered in the lab.

Currently, we do not fully understand the extent to which environmental stimulation and movement-related information recruit attention resources. However, based on the findings presented here and in other recently published naturalistic studies [2,21] it is becoming increasingly evident that factors such as gross motor activity (as opposed to sitting or standing), cognitive task difficulty, and the degree of experimental control over ambient conditions (i.e. laboratory vs. real-world settings), seem to be highly relevant determinants of attention and cognitive resource allocation. Such results highlight potential limitations in the generalizability of standard laboratory experiments to the more complex, dynamic conditions encountered in everyday life. However, it is also important to note some of the limitations and ongoing challenges faced by real-world designs, which we consider below.

The present study focused on EEG signals in order to avoid potential complications or confounds introduced by encumbering the participant with multiple measurement devices. One consequence of this decision was that we were unable to augment our analysis of cognitive task performance with information concerning gait parameters. However, previous findings have indicated that competing cognitive tasks may lead to a decline in gait performance [57]. Furthermore, it has been shown that people tend to prioritize cognitive tasks over gait, to the extent that even a risk of falling is accepted in order to maintain the successful execution of the

cognitive task (e.g., conversation) [58,59]. In the present context, it can only be speculated that gait parameters may have changed with increased complexity of the situation (across the campus vs. around the sports field) and thereby, the amount of attention focused on the cognitive task could be maintained; however, this must remain a question for future research.

Moreover, while advancing technological innovations are revolutionizing the study of cognition under ecologically-valid conditions, mobile EEG designs still face a number of challenges. In addition to the concern that performing tasks and activities while wearing/carrying recording devices may perturb normal functioning, the amount and quality of the data collected under such conditions is often reduced compared to standard laboratory conditions. Although we attempted to mitigate this potential issue through the application of sophisticated artifact rejection techniques, five participants were excluded from analysis due to high rates of rejected data. The problem of noisy data collection might also have been compounded by the measurement imprecision introduced by the delayed (and in some cases, repeated) transmission of event markers. While we took care to correct these errors without introducing bias (i.e., applying a uniform adjustment designed to ameliorate event marker lag across all conditions prior to statistical analysis), the additional variance introduced into the data may have limited our sensitivity to fine-grained differences between conditions.

While real-world EEG studies are still in their infancy and faced with a number of limitations, they are beginning to provide novel insights concerning the nature of well-established markers of cognitive processing such as the MMN and P3 components. The present results align well with recently published mobile EEG studies and fill an important gap in this literature about the effects of environmental complexity, motor demands, and cognitive task load on attention within naturalistic scenarios. Furthermore, our findings highlight the necessity of extending future cognitive research programs beyond the confines of the laboratory. Ideally, such studies will combine complementary measurement devices as they become increasingly portable (e.g., ear-EEG & Eye-tracking), and address a greater variety of everyday situations.

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