Aiming at ecological validity—Midfrontal theta oscillations in a toy gun shooting task

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Abstract
Laboratory electroencephalography (EEG) studies have already provided important insights into the neuronal mechanisms of performance monitoring. However, to our knowledge no study so far has examined neuronal correlates of performance monitoring using an ecologically valid task outside a typical laboratory setting. Therefore, we examined midfrontal theta and the feedback-related negativity (FRN) using mobile EEG in a physical shooting task within an ecologically valid environment with highly dynamical visual feedback. Participants shot a target using a toy gun while moving and looking around freely. Shots that missed the target evoked stronger midfrontal theta activity than hits and this response was rather phase-unlocked. There was no difference between misses and hits in the FRN. The results raise the question whether the absence of certain ERP components like the FRN could be due to methodological reasons or to the fact that partially different neuronal processes may be activated in the laboratory as compared to more ecologically valid tasks. Overall, our results indicate that crucial neurocognitive processes of performance monitoring can be assessed in highly dynamic and ecologically valid settings by mobile EEG.

KEYWORDS
ecological validity, FRN, mobile EEG, performance monitoring, theta

1 | INTRODUCTION

Every day our brain has to continuously deal with vast amounts of highly dynamical input. When examining cognition, neuroscientists traditionally try to isolate cognitive processes in order to exclude disturbing influences. Advances in neuroscientific technology enable us to transfer the knowledge gained in the laboratory into more ecologically valid settings and to investigate to what extent these neuronal processes occur under less controlled circumstances (Ladouce et al., 2016; Parada et al., 2020).

One aspect that has been more or less neglected within this approach so far is that of performance monitoring. Successful goal-directed behaviour requires continuous assessment of ongoing actions and their consequences. Evaluation of adequacy and success of actions is essential for learning and executing appropriate and optimal behaviour (Ridderinkhof et al., 2004). Performance monitoring systems search for

Abbreviations: aMCC, anterior midcingulate cortex; EEG, electroencephalography/electroencephalogram; ERP, event-related potential; FMθ, Midfrontal theta; FRN, feedback-related negativity; ITPTC, inter-trial phase coherence; rMANOVA, repeated measurements analysis of variances; RPE, reward-prediction-errors; SEM, standardized error of the mean; SNR, signal-to-noise ratio.

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deviations of expected outcomes from the actual outcomes. Upon detecting deviations, adaptations are initiated in the sense of a feedback loop (Ullsperger et al., 2014).

Laboratory EEG-research on performance monitoring has revealed insights into neuronal correlates of the underlying mechanisms, with many studies focusing on error processing and associated need for adaptation. For many daily actions humans perform, external feedback about the outcome is needed to detect errors. Feedback processing is a specific kind of performance monitoring which has been investigated in hundreds of typical laboratory EEG studies (Ullsperger et al., 2014), using various kinds of tasks like time estimation tasks (Gruendl et al., 2011; Holroyd & Krigolson, 2007; Miltner et al., 1997), gambling tasks (Gehring & Willoughby, 2002; Hajcak et al., 2006) or reinforcement learning tasks (Osinsky et al., 2018; Reiter et al., 2016).

Within this framework, the signalling of reward-prediction-errors (RPEs) in the anterior midcingulate cortex (aMCC) has been associated with the feedback-related negativity (FRN), a fronto-central negative-going deflection about 200–350 ms after a negative compared to a positive outcome (Baker & Holroyd, 2011; Gehring & Willoughby, 2002; Hauser et al., 2014; Holroyd & Umemoto, 2016; Holroyd & Yeung, 2012; Miltner et al., 1997; Osinsky et al., 2012). The FRN is thought to reflect a signed reward prediction error (Holroyd et al., 2004), which results from a difference between the expected and the actual outcome and is used to adjust the expected outcome value in subsequent trials (Walsh & Anderson, 2012).

The FRN has been associated with frontomedial theta band oscillations (FMθ; Cavanagh et al., 2010). FMθ appears to represent a need for control signal generated by the midcingulate cortex and pre-supplemental motor area. Regarding performance monitoring, FMθ is evoked by surprising or negative external feedback signalling conflict or errors (Cavanagh & Frank, 2014). Accordingly, negative feedback evokes stronger FMθ than positive feedback (Bernat et al., 2015; Cavanagh & Frank, 2014; Cavanagh et al., 2010, 2012; Cohen, 2011; Cohen & Donner, 2013; Cohen & van Gaal, 2014; Crowley et al., 2014; Di Luft et al., 2013; Hoffmann et al., 2014; Osinsky et al., 2016; van de Vijver et al., 2011).

FRN and FMθ have been shown to be sensitive to situational factors like outcome frequencies and expectancies (Cohen et al., 2007; Holroyd et al., 2004; Osinsky et al., 2016; Yasuda et al., 2004), reward magnitude and type (Hajcak et al., 2006; Holroyd et al., 2006; Osinsky et al., 2017; Weinberg et al., 2014), control over the outcome (Sambrook & Goslin, 2015) or cognitive effort and attention (Hsieh & Ranganath, 2014; Mitchell et al., 2008). Laboratory investigations generally allow these factors to be controlled. Further, researchers can control participants visual input and obtain millisecond accurate information about timings within computer-based experimental designs. This is fundamentally important, with especially ERPs being sensitive for jitter in latencies on single trial level, as temporal inaccuracies may distort the averaged ERPs (Luck, 2014). Time-frequency analyses can to some extent make up for this weakness of time-domain analyses. They are not as sensitive to smaller inaccuracies in timing precision based on the underlying temporal smoothing leading to a generally lower temporal precision for time-frequency analyses than for ERP analyses (Cohen, 2014). From a methodological point of view, time-frequency analyses can complement ERP analyses in another way by their ability to detect non-phase-locked electrocortical signals (Cohen, 2014).

Taking the step out of the laboratory, mobile EEG assessment allows transferring common paradigms into more dynamic settings. For instance, a very prominent ERP component, the P300, was replicated in auditory oddball tasks without a standardized survey situation and a shielded EEG cabin but with participants standing, walking (Debener et al., 2012; Reiser et al., 2019) or cycling indoors and outdoors (Scanlon et al., 2017), controlling cars (Protzak & Gramann, 2018) or planes (Dehais et al., 2019). These examples demonstrate that mobile EEG measurement is capable of enabling access to the working human brain in real life situations. In these studies, the ecological validity of the situation is enhanced. However, the tasks themselves remained artificial and were more or less separated from the surrounding environment.

Another approach is not to only observe brain activity in situations that are dynamic, but brain activity directly related to dynamic actions. For example, higher sensorimotor rhythm power was found in expert dart players when preparing for a dart throw compared to novice players (Cheng et al., 2015) and a contingent negative variation seems to be an indicator of cognitive motor control when preparing for a throw in a physical throwing task within a virtual environment (Frömer et al., 2012).

Regarding performance monitoring, Frömer et al. (2016) used a similar throwing task utilizing a virtual environment to observe correlates of performance monitoring outside of a standard laboratory approach. Observing the successful trials, they found a frontocentral positive going deflection, the so-called reward positivity, which can be considered as the counterpart of the FRN. Frömer et al. were able to show common moderating effects on the reward positivity like reward magnitude, expectancy or the impact of preceding trials and therefore replicated findings well known from the laboratory using a more ecologically valid task. Yet, to some extent the environment remained artificial, lacking ecological validity in a different meaningful part of the experiment.

The goal of the present study is to combine both approaches and observe brain activity via mobile EEG in a holistic, ecologically valid performance monitoring task within a little restricted, ecologically valid environment with highly
dynamical visual input. To the best of our knowledge, this is the first EEG study on performance monitoring explicitly addressing the ecological validity of the task and the setting at the same time. For that purpose, participants shot targets with a toy gun moving and looking around freely while wearing a mobile EEG-system. We have deliberately omitted established measurement preconditions such as an electronically shielded cabin, controlled visual input or instructions to reduce movement or blinking. The examined action and environment should reflect, as accurately as possible, what using a toy gun would feel like at home and for fun.

In accordance with the literature from laboratory studies, we expect to observe greater FMθ power after misses than after hits, as in case of missing a target an adjustment is necessary for the following shot (Cavanagh & Frank, 2014). In consideration of the diversity of the visual input and the assumed variety of involved cognitive processes in this setting, time-frequency analyses of EEG data may allow to detect effects we may miss in classical time-domain ERP analyses, due to the issues already mentioned above. As there is evidence that midfrontal theta oscillations may not be phase-locked to a stimulus (Cohen & Donner, 2013) we further distinguish between non-phase-locked and phase-locked oscillatory power to examine whether the effect of greater FMθ power after misses is reflected in both non-phase-locked oscillatory power and phase-locked oscillatory power. Further, we assess inter-trial phase coherence (ITPC) of theta oscillations. ITPC is a measure of phase consistency across trials in order to quantify the degree to which brain activity shows time- and frequency-dependent synchronization to an event (Malone et al., 2017). Lastly, we expect to see an FRN effect in the EEG time-domain with more negative FRN amplitudes after misses compared to hits.

2 | Methods

2.1 | Participants and general procedure

Twenty-three students from the University of Osnabrück took part in this study and received course credit for participation. EEG data of one student has not been recorded completely, therefore data of 22 participants are included in the analysis (14 women, 8 men, mean age = 21.91, SD = 2.96). All had normal or corrected-to-normal vision and reported to be free of any psychiatric or neurological disorders. The study was approved by the local ethics committee and all participants gave written informed consent.

2.2 | Shooting task

Participants repeatedly shot a target with a toy gun (Nerf© by Hasbro), using foam darts flying with a speed of approximately 50 kmph. Each participant shot 19 magazines of 6 darts each, resulting in 114 shots. The target was round and had a diameter of 25 cm. The shooting distance varied from 1.0 to 5.0 m (mean = 3.20, SD = 0.93). As the FRN is sensitive to unequal outcome frequencies (Sambrook & Goslin, 2015), after each magazine the distance of the participant to the target was adjusted in order to achieve approximately 50% hits and 50% misses. Therefore, if participants had a hit rate smaller than 40% after finishing a magazine they shot the next block 0.5 m closer to the target. If their hit rate was greater than 60%, they shot the next block from 0.5 m further away. This procedure resulted in a hit rate of M = 50.64% (SD = 5.08).

The target was equipped with piezo sensors (Adafruit) for detecting the time of impact of the foam darts. The sensors showed to recognize 97.69% of the shots correctly. Shots that were not recognized correctly were not included in the analysis and instead made up for with additional shots. The sensors were attached to a Raspberry Pi 3® (Raspberry Pi Foundation) that was time-synchronized with the EEG data stream via LabStreamingLayer (LSL) to precisely time-lock the events registered by the sensor data to the EEG data.

In order to get similar triggers for shots that miss the target, the target was attached to the middle of a 1.0 ×0.8 m plate representing a zone for those misses. The plate was equipped with separate sensors allowing determining the time when the dart is at the height of the target but actually misses it. In the rare case of a dart being shot so far off that it does not even hit this "miss-zone," this dart was deliberately not detectable. With these shots way off target, we do not know to what extent deviating cognitive and perceptual processing may take place, so those trials were not included in the analysis and instead made up for with additional shots (Figure 1 for experimental setting).

2.3 | EEG recordings and preprocessing

EEG was recorded using a 32-channel wireless mobile EEG system (LiveAmp 32) and BrainVision Recorder Software (all Brain Products GmbH). Electrodes were placed according to the international 10–20 system. The sampling rate was 500 Hz. During recording, the signal was band-pass filtered (0.016–250 Hz). All sites were referenced online to FCz. The ground electrode was placed at AFz. All electrode impedances were kept below 15 kΩ.

Offline preprocessing was conducted via BrainVision Analyzer software (Brain Products GmbH) and Matlab (MathWorks Inc.). Data were re-referenced to the mean of all electrodes and former reference FCz was reinstated as additional data channel. EEG data were filtered with a 0.1 Hz high-pass filter and a 30 Hz low-pass Filter (zero phase shift Butterworth filters, 30 Hz as 3 dB point, 8th order). An automatic independent component analysis (ICA) based
correction method implemented in BrainVision Analyzer 2.0 (Brain Products GmbH) was conducted for correction of ocular artifacts. In detail, we used an automatic Restricted Fast ICA-based eye movement correction, computing a correlative score between component activations and the activity of electrooculogram (EOG) channels. Data were back-transformed from the component to the channel-space, excluding those components for which the sum of squared correlation with EOG exceeded 0.10 (i.e., more than 10% of shared variance with EOG; mean number of deleted components = 2.05; SD = 0.21).

Continuous EEG was segmented into 2,000 ms epochs around the trigger moment of a hit or a miss (−1,000–1,000 ms). Segments containing voltage steps greater than 150 μV/ms or maximum-minimum differences of 200 μV or larger were rejected from further analysis.

Remaining segments were transformed using a family of complex morlet wavelets from 1 to 30 Hz in 30 logarithmic steps. These modulated Gaussian sine functions are defined as: \( \psi(t,f) = Ae^{-\tau^2/2\sigma^2}e^{i\omega f t} \) with \( A = \frac{1}{\sqrt{\tau \sqrt{2\pi}}} \) and window factor \( \frac{\tau}{\sigma} = 6.7 \). Resulting power levels for each frequency layer were then baseline-corrected using a decibel (dB) transform: dB power = 10×log\(_{10}\left( \frac{\text{Power}}{\text{baseline}} \right) \) with baseline power defined as the average power in the –800 to –200 ms time window across all conditions. Segments were averaged for each participant and condition of interest.

These data are referred to as total oscillatory power. In order to be able to separate phase-locked and non-phase-locked oscillatory power, we calculated non-phase-locked oscillatory power by subtracting the condition-wise ERP from each trial before applying time-frequency transformation. This is a common approach of removing phase-locked activity which has previously also been used for assessing FMθ (e.g., Cohen, 2014; Cohen & Donner, 2013; Duprez et al., 2020). To calculate phase-locked oscillatory power we then subtracted non-phase-locked power from total power after applying time-frequency transformation and dB-correction separately to total power and non-phase-locked power.

ITPC was estimated per electrode as:

\[
\text{ITPC}(t,f) = \left| \sum_{r=1}^{n} e^{ik_{tr}} \right| \quad \text{with } n = \text{number of trials and } k = \text{phase angle on trial } r \text{ at time-frequency point } tf
\]

(Cohen, 2014). Therefore, an ITPC value of 0 would mean that there is a uniform distribution of phase across trials at time t, and a value of 1 would mean that the phase at time t is identical for each trial.

ERPs were calculated for the same segmented time windows, baseline corrected (−200 to 0 ms) and averaged for each participant and condition of interest. For ERP analyses a different time window for baseline computation was applied as this baseline window is well established for FRN analysis (Sambrook & Goslin, 2015) and bears the
advantage of being temporally closer to the phenomenon of interest (Luck, 2014).

Based on the literature, FMθ was quantified as mean power from 4.09 to 7.34 Hz at FCz in the time window from 200 to 300 ms after the impact of the dart, comparable with windows used in previous studies (Cavanagh et al., 2010; Cohen & Donner, 2013; Hajihosseini & Holroyd, 2013) and corresponding to the time window used for FRN analysis within this study. Two-tailed t-tests for paired samples were conducted on FMθ to assess differences in oscillatory power separately for phase-locked and non-phase-locked activity. For ITPC estimates a two-tailed t-test for paired samples comparing mean ITPC for hits and misses was conducted.

Based on the literature FRN was quantified as mean activity at FCz within 200 to 300 ms (Holroyd & Umemoto, 2016; Walsh & Anderson, 2012). For FRN a two-tailed t-test for paired samples comparing mean FRN amplitudes for hits and misses was conducted.

Effect sizes were calculated in terms of partial eta squared for the rmANOVA and in terms of Cohen’s d for t-tests. Estimates for signal-to-noise ratio were calculated in terms of $\text{SNR} = \frac{\text{Mean score}}{\text{SEM}}$ with $\text{SEM} = \text{standardized error of the mean}$. Using this approach SNR represents the ratio of the signal of interest (FMθ power or FRN amplitude) to its measurement error (Cohen, 2014; Luck et al., 2020).

3 | RESULTS

Signal-to-noise ratios for time-frequency data range from $\text{SNR} = 8.53$ for hits to $\text{SNR} = 10.16$ for misses. Signal-to-noise ratios for ERP data range from $\text{SNR} = 8.97$ for hits to $\text{SNR} = 7.40$ for misses, pointing to a good data quality for time-frequency domain and time-domain data.

The t-tests on time-frequency data revealed strongly increased FMθ after misses compared to hits in non-phase-locked activity ($t(21) = 5.77, p < .001, d = 0.123$) and a moderate corresponding increase in phase-locked activity ($t(21) = 2.49, p < .021, d = 0.53$). Time-frequency plots of total, non-phase-locked and phase-locked power for the difference of misses minus hits are displayed in Figure 2.

ITPC estimates were generally small but showed a significant difference between conditions ($t(1,21) = 2.71, p = .013, d = 0.58$) with stronger ITPC for misses ($M = 0.32, SD = 0.13$) than for hits ($M = 0.24, SD = 0.09$). The

FIGURE 2  Time-frequency plots for oscillatory power at FCz. Plots depict the differences of missing shots minus hits in relation to the impact of the dart. Scalp topography of the differences is plotted for mean theta activity at 200–300 ms.
differences in ITPC for misses minus hits are displayed in Figure 3.

The $t$-test on mean FRN amplitudes did not yield a significant difference for hits and misses ($t(1,21) = 1.48, p = .154, d = 0.32$). ERPs are displayed in Figure 4.

Upon visual inspection of the data, we detected a notable descriptive effect for greater delta power after hits compared to misses in phase-locked activity. For exploratory analyses we examined mean power in phase locked-activity from 1 to 2.87 Hz at FCz in the time window from 300 to 700 ms in which the effect was most pronounced. We found a large effect of stronger delta power after hits compared to misses ($t(21) = 3.55, p < .01, d = 0.76$). ITPC estimates for delta oscillations were higher than for theta oscillations and showed a significant difference ($t(21) = 3.81, p < .001, d = 0.81$) with stronger ITPC for hits ($M = 0.61, SD = 0.13$) than for misses ($M = 0.53, SD = 0.16$). As phase-locked delta gets linked to feedback-related P3 generation (Bernat et al., 2015; Glazer et al., 2018; Harper et al., 2014, 2017; Makeig, et al., 2004; Rawls et al., 2020; Watts et al., 2017) we further analysed mean amplitude in the time-domain within the same time window (300 to 700 ms). We found a moderately stronger positivity after misses than after hits ($t(21) = 2.87, p < .05, d = 0.61$). Topographies of P3 and phase-locked delta for the according time window are displayed in Figure 5.

4 | DISCUSSION

The aim of this study was to examine FRN and feedback related FMθ in a little restricted setting utilizing a dynamical performance monitoring task. While we did not observe the
well-known FRN effect in the time domain, we were able to replicate an increased FMθ response to negative action outcomes in the time-frequency domain. Our results therefore suggest that event-related oscillatory activity can be obtained by mobile EEG recording in such a non-standard laboratory experiment. For ERP analysis further adjustments seem to be needed.

In particular, our results show that FMθ power in response to the impact of the dart was stronger for misses than for hits. In general, these results correspond to common findings about stronger FMθ after negative compared to positive outcomes (Bernat et al., 2015; Cavanagh & Frank, 2014; Cohen, 2011; Cohen & van Gaal, 2014; Crowley et al., 2014; Di Luft et al., 2013; Duprez et al., 2020; Hoffmann et al., 2014; Osinsky et al., 2016; van de Vijver et al., 2011).

Interestingly, we found stronger FMθ power especially in phase-locked activity while the effect was smaller in non-phase-locked activity. Cohen and Donner (2013) found similar results in a conflict task, indicating that a major proportion of task-related midfrontal EEG signal reflects a modulation of theta oscillations induced by, but not phase-locked to events that call for an increased need of cognitive control. In this regard, differences in power that are rather little phase-locked to an event and are band-limited to the theta frequency may be directly generated by neural oscillations (David et al., 2006). This may indicate that non-phase-locked FMθ and neurocognitive processes measured by ERPs like the FRN do not represent different reflections of the same underlying neural process but rather autonomous reflections of dissociable neural processes (Cohen & Donner, 2013; David et al., 2006; Holroyd & Umemoto, 2016; Osinsky et al., 2016).

However, our ITPC estimates for FMθ show that there is some degree of phase-locking in both conditions with stronger phase-locking after misses. While the neural basis of ERP generation is still a matter of debate, this might be associated with ERP generation partly through event-related phase resetting of ongoing oscillatory activity which would imply similar neural sources for FMθ and associated ERPs (Fell et al., 2004; Makeig et al., 2004, 2002; Min et al., 2007; Thatcher, 2012).

Nonetheless, our results regarding phase-locking open up questions for further research. As we were not able to detect an FRN within this approach, this issue might apply to more ERPs and obstruct determining completely phase-locked activity based on a subtraction of the ERP. This would lead to an underestimation of the proportion of oscillatory power that is phase-locked. ITPC estimates, even though mathematically independent from amplitude, may be biased by the differences in power between the conditions, simply due to cleaner phase estimation based on higher amplitudes or also due to variance in temporal latencies (Cohen, 2014; van Diepen & Mazaheri, 2018). For those reasons, these results have to be interpreted carefully and point out challenges within the MoBI research approach that require new solutions for additional research.

FMθ, in our case evoked by the dart missing the target, may reflect the utilization of the prediction error in favour of behavioural adaptation (Cavanagh et al., 2010; Holroyd & Umemoto, 2016). One key aspect of this study is the nature of behaviour to be adapted. The performed action (i.e., shooting a toy gun) represents a holistic activity based on a natural intrinsic motivation to hit the target, as there are no further external rewards. Accordingly, the task exemplifies a performance monitoring process that may run similar in real life.

In exploratory analyses, we found significantly greater delta power after hits compared to misses in phase-locked activity. In addition, there is solid ITPC for delta in both...
conditions. This sensitivity of phase-locked delta to positive rewards is in line with findings of several studies (Bernat et al., 2015; Cavanagh, 2015; Glazer et al., 2018; Li et al., 2016; Me et al., 2018; Watts et al., 2017; Webb et al., 2017). It has been linked to elaborate feedback processing evaluating multiple feedback attributes, both primary characteristics of reward feedback (gain/loss) and secondary characteristics (e.g., magnitude or frequency) (Bernat et al., 2015; Glazer et al., 2018; Me et al., 2018). Theta band activity and delta band activity seem to contribute to feedback processing independently. While FMθ has been specifically associated with FRN generation, delta activity has been linked to feedback-related P3 generation additionally to FRN generation (Glazer et al., 2018). We found differences in P3 amplitudes as well. The topographies of these differences partially match those of the differences in delta power at central electrode sites but they show to extend into frontopolar regions, differing from previous findings. Therefore, these preliminary findings indicate the need for further research to assess their underlying functionalities.

Generally, a single dart shot within our paradigm comes with a multitude of dynamical visual input and feedback, which has to be cognitively processed and integrated. When dealing with such variety of information FMθ is just not sufficient for comprehensively reflecting the cognitive processes involved. Accordingly, delta activity can reflect further evaluative processes. This finding again emphasizes the importance of ecologically valid tasks and experimental settings in order to be able to examine human brain functionality in its everyday functioning in comparison to its functionality in specific laboratory tasks.

In regard to the mobile EEG approach the replication of a common EEG signature, in our case FMθ, within this little restricted environment falls in line with other findings of mobile EEG research realizing dynamical settings (Cheng et al., 2015; Debener et al., 2012; Dehais et al., 2019; Frömer et al., 2012, 2016; Maurer et al., 2015; Protzak & Gramann, 2018; Reiser et al., 2019). This literature shows that it is possible to receive satisfying EEG measurements while systematically reducing established limitations. However, to our knowledge this is the first study on performance monitoring explicitly transferring a dynamical task into a setting with highly dynamical visual input. Linking ecological validity of the task and ecological validity of the setting closes a gap and takes a step towards a research approach that tries to implement an improvement in ecological validity in every aspect of the experiment. Relying on this basis, future dynamical and ecologically valid EEG research will be able to go beyond replication studies and instead investigate actions, situations, effects and research questions that are merely not accessible in laboratory.

Yet, the present study points out limitations to reducing research restrictions. Leaving a standardized laboratory setting, we have to face new problems. One of the most important aspects to keep in mind may be that the darts shot spend some time in the air before hitting the target. Within this time, participants can track the darts and could infer the outcome. In difference to previous studies, we cannot exactly determine which information is available for the participant at a given time. This may lead to different onsets of cognitive processing and single trial ERPs accordingly. With ERPs being sensitive to jitter in latencies, the potential differences in single trial ERP onsets may be one reason why we were not able to find a typical FRN effect.

However, those anticipatory processes are part of the natural cognition and therefore should be part of investigations aiming at ecological validity. Factors like projectile velocity could be manipulated systematically in future studies in order to observe natural anticipatory processes. Furthermore, robustness of ERP components can be assessed simultaneously by adding a specified amount of simulated jitter to the EEG signal to see whether they can still be found, maybe even depending on the time length of the anticipatory window.

As this is, to our knowledge, the first study on event-related performance monitoring components in such a little restricted setting, we focused on examining according central neuronal correlates. There are many questions pending for future research that would be highly interesting to observe in this little restricted behaviour. Within this first setup, we were not able to map typical intraindividual effects like effects of difficulty or post-error slowing. As participants had no regulations on how to behave between the shots, common indicators like inter-trial intervals may not be as meaningful. Nonetheless, even in a little restricted setting we can design our instructions and setup in a way that we can derive these parameters. By adding additional sensors for example to the trigger of the gun assessing the actual motor act or even using motion capture to further assess the participants behaviour we can record relevant factors and behaviour rather than experimentally control it. This way we can end up with much more information than we could gather in settings that are more restricted.

5 | CONCLUSION

The present study implemented a performance monitoring paradigm using a holistic task within a little restricted experimental setting investigating event-related EEG signatures. It conformed previous findings on FMθ while showing limitations to assessing phase-locked oscillations and FRN. Overall, our results close a gap between other findings of mobile EEG research focusing on either ecological validity of the setting or of the task while this study enhances both at the same time.
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CONFLICT OF INTEREST
The authors declare no competing interests.

AUTHOR CONTRIBUTIONS
L.L. and R.O. conceptualized the study. L.L. developed the study design and wrote the manuscript. L.L. collected and analysed the data. R.O. supervised the study. All authors approved the final version of the manuscript for submission.

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DATA AVAILABILITY STATEMENT
The EEG data that support the findings of this study are available on OSF (https://osf.io/82ur5/?view_only=5430472e7d134be6a08f4864218a8a8d).

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