Eye Blink-Related Brain Potentials During Landmark-Based Navigation in Virtual Reality

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Abstract

Landmarks support navigation and spatial learning of environments by serving as cognitive anchors. However, little research has been done to investigate how the design of landmarks on mobile maps affects cognitive processing. To address this gap, the present study utilized a within-subjects design to experimentally examine how three different landmark densities (3 vs. 5 vs. 7 landmarks) on mobile maps influence users' spatial learning and cognitive load during navigation. Cognitive load was measured using electroencephalography (EEG). We applied an event-related analysis approach by utilizing eye blinks as naturalistic event markers to segment the EEG data. Results demonstrate that showing five landmarks along a given route to follow on a mobile map, compared to three and seven landmarks, improved spatial learning performance without taxing more cognitive resources. Our study shows that users' cognitive load and spatial learning outcomes should be considered when designing landmark-based navigation assistance systems.

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1 Background

1.1 Landmark-based navigation assistance

GPS guidance is increasingly used to facilitate navigation and wayfinding, especially in an unfamiliar environment. Navigators follow turn-by-turn directions given in real time. However, the increased use of mobile maps has been shown to negatively affect landmark and route learning of an environment [4]. Including landmarks in navigation assistance systems has been proposed to facilitate users' learning of their surroundings by serving as cognitive anchors. For example, navigators could use landmarks to determine their current location and remember key decision points along routes. However, using landmarks as mnemonic devices entails additional cognitive processing, which could additionally affect individuals' cognitive load during navigation. Indeed, previous studies have found that learners have limited cognitive capacity – typically four items (or chunks) and that their cognitive load increased as the number of items to be remembered increased [5]. We thus investigated how the number of landmarks on mobile maps affected navigators' cognitive load during navigation. Based on cognitive capacity theory, we defined low, medium, and high landmark density visualized on mobile maps as three, five, and seven landmarks, respectively.

1.2 Assessing cognitive load through brain activity

Previous research has used performance on dual task or/and pupil dilation to measure cognitive load. However, these measures are an indirect approach to assess cognitive processing. We thus turned to electroencephalography (EEG), an established method that directly measures real-time cognitive load unobtrusively. EEG recordings of brain activity typically require event markers that indicate when notable events such as stimulus presentation or participant responses occur. These markers allow the segmentation of EEG data according to these events for event-related analysis. However, the presentation of additional stimuli may interrupt participants' task performance in naturalistic settings. A different set of event markers is therefore needed when examining brain activity during wayfinding in naturalistic settings.

1.2.1 Eye blinks as event markers in naturalistic settings

Previous research has found that spontaneous eye blinks are suppressed during periods of high cognitive load, and especially during the processing of complex visual scenes [6]. This makes eye blinks particularly useful as indicators of cognitive load in wayfinding, where individuals perform a continuous task without interruption from artificially introduced stimuli [6]. Among the studies that investigated the relationship between eye blinks and cognitive load, consistent evidence has emerged. It was shown that the rate of eye blinks decreases during cognitively demanding tasks [1]. Most research linking eye blinks to cognitive load had focused on characteristics of eye blinks such as blink rate and deflection. Less research studied cognitive load by analyzing brain activity related to eye blinks [6]. Therefore, more research is needed that investigates brain activity during eye blinks when individuals perform cognitive tasks.

1.2.2 Blink event-related potentials (bERPs)

A previous study examined bERPs when participants were performing a cognitive task versus a physical task or during rest [6]. The authors found a significantly more pronounced P1, a positive component 100 ms after blink maximum, in the occipital region (Oz) and N2, a negative component around 200 ms after blink maximum, in the fronto-central region (Fz and FCz) during the cognitive task. An increase in stimulus-evoked P1 amplitude in occipital regions indicates a higher allocation of attentional resources during early visual processing. An increase in stimulus-evoked N2 amplitude is associated with the involvement of cognitive control [3]. Another stimulus-evoked ERP component that has been associated with cognitive load is the P3, a slow wave that appears with a maximum amplitude above the parieto-occipital region (Pz, POz and Oz). Previous studies have shown that the parietal P3 component is a reliable indicator for resource allocation during cognitive processing and a valid index of cognitive load. Increased cognitive load requires more resources for cognitive processing, leading to an increased P3 amplitude (Fig. 1).

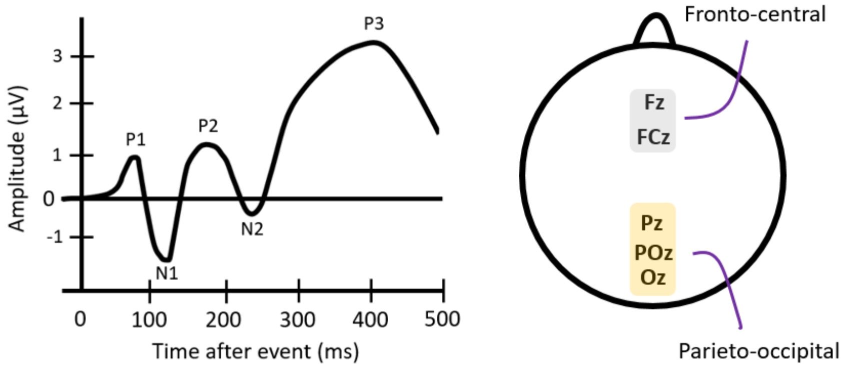

Figure 1 Left panel: A waveform showing ERP components including the P1, N2, and P3. Adapted from `https://en.wikipedia.org/wiki/Event-related_potential`. Right panel: Head map showing the positions of the electrodes of interest in the fronto-central (highlighted in gray) and parieto-occipital (highlighted in orange) regions.

1.3 The present research and hypothesis

The present study investigated how the number of landmarks displayed on a mobile map affects navigators' cognitive load during landmark-based navigation. We hypothesized that a higher number of landmarks displayed on a mobile map would increase cognitive load during a landmark-based navigation task due to increased cognitive resources used to process excess visual and spatial information. Increased cognitive load would be indicated by more pronounced amplitudes in the following blink-related components: the P3 amplitude at the parieto-occipital region, the N2 amplitude at the fronto-central region, and the P1 amplitude at the occipital region. We also hypothesized that spatial learning performance would initially increase from the 3- to 5-landmark conditions and decrease from the 5- to 7-landmark conditions due to increased cognitive load [2].

2 Method

2.1 Participants and experimental design

Forty-eight participants (29 females) with age ranging from 18 to 35 years (M = 25.6 yrs, SD = 4.09) took part in the study. Three participants were excluded because of noisy or missing data due to technical issues, resulting in an analyzed sample of 45 participants. We adopted a within-participant design with three conditions, showing either 3, 5, or 7 landmarks on the mobile map while participants navigated a predefined navigation route (Fig. 2a) in three virtual cities. The three navigation routes consisted each of five intersections and were similar in length (approximately 900 m each). Each route contained seven salient buildings as landmarks: the starting building (home), five landmarks at the five intersections, and the destination building (goal). The landmarks were visualized as either 3D realistic or green rectangles according to landmark-density condition. The three conditions were evenly distributed across the three cities.

2.2 Procedure

Participants were asked to navigate as quickly as possible to a predefined destination and to learn the landmarks displayed on the map. Three virtual cities were designed in ArcGIS City Engine 2018.0 and displayed on a three-sided, stereo cave automatic virtual environment (CAVE) using Unity 2018.4 LTS (Fig. 2b). Participants moved by using a foot-operated controller (Fig. 2c) through the virtual environment displayed in the CAVE. Each city contained a pre-defined route to be followed. The route, including start and destination locations, was shown on a mobile map projected in the center screen of the CAVE during navigation. This map indicated navigators' current location and provided turn-by-turn instructions. The map appeared before and after each intersection, and along straight segments of the followed route. The map rotated along with the navigators' heading direction. After navigating in each city, participants' spatial knowledge was tested using a landmark recognition task, a route direction task, and a Judgements of Relative Direction (JRD) task. While participants were performing the navigation task, their brain activity was measured using a 64-channel EEG device with active electrodes (LiveAmp, Brain Products GmbH, Gilching, Germany). EEG was recorded at a 500 Hz sampling rate with a 131 Hz low-pass filter with input impedance set at below 10 kOhm.

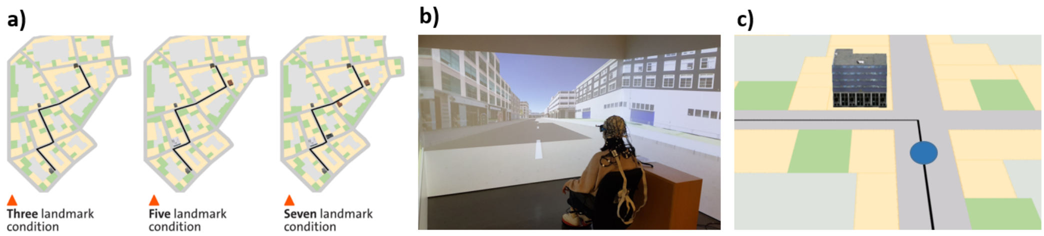

Figure 2 a) Three landmark density conditions in one city. The left, middle, and right figures represent the map condition with three, five, and seven landmarks visualized on the map respectively. b) A participant sat on a chair 30 cm away from the center of the VR system (CAVE), placed her feet on a foot-operated controller, and had her brain activity recorded with EEG during the navigation experiment. c) A track-up map providing a navigator's current location (blue dot), the route direction to follow (black line), and, depending on the landmark density condition, a 3D landmark at the intersection.

2.3 Data processing and analysis

For more details of EEG data preprocessing, please see the appendix A: EEG data preprocessing.

To detect and extract brain activity related to eye blinks, we followed the protocol established by Wunderlich and Gramann [7]. Eye blink events were created by peak detection in the time series of the IC representing vertical eye movements. Next, we removed all independent components from the data that were classified as unlikely to represent brain activity (probability below 30%) and then back-projected the remaining data to the sensor level. To extract bERPs, we used the Unfold toolbox. Information on the different landmark density conditions (3, 5, and 7 landmarks) was entered into the regression formula $y = 1 + cat(landmark)$, which was then solved to obtain the intercepts and beta values (baseline-corrected at -500 to -200 ms preceding the blink event) for each condition. Of the beta values computed, we extracted those corresponding to the bERP components of interest (P1, N2, and P3) at the electrodes of interest (Fz, FCz, Pz, POz, and Oz) for statistical analysis. The P1 at Oz was extracted from within 110–150 ms after blink maximum. The N2 amplitude was extracted from 250–390 ms after blink maximum and averaged between Fz and FCz. The P3 was extracted from 250–340 ms after blink maximum and averaged between Pz, POz, and Oz. We performed one-way repeated measures ANOVAs with landmark condition as the within-subjects predictor (3 vs. 5 vs. 7 landmarks) on each of the bERP components of interest.

3 Results

3.1 Behavioral results

Multilevel regression modeling was conducted to compare spatial learning performance between the three landmark density conditions in R 4.1.0. The spatial learning result shows that landmark recognition and route direction memory improves when the number of presented landmarks increases from three to five ($beta = 0.51$, 95%CI [0.30, 0.72], $p < 0.001$), while learning performance does not increase further when seven landmarks are depicted on the map ($beta = -0.11$, 95%CI [−0.32, 0.10], $p = 0.31$).There is no significant effect of the number of landmarks on performance on the JRD. More details on results related to behavioral performance are reported in Cheng et al. [2].

3.2 EEG results

The analysis of P1 at Oz shows no significant differences between the conditions, $p = 0.568$. Analysis of the N2 also reveals no significant differences between the conditions $p = 0.660$. Lastly, analysis of the P3 in the parieto-occipital region reveals significant differences between the conditions, $F(2, 44) = 3.72$, $p = 0.028$. Post-hoc contrasts reveal that P3 amplitude in the 7-landmark condition ($M = 3.24$, $SD = 1.99$) is significantly higher compared to the 5-landmark condition ($M = 2.75$, $SD = 1.79$) ($ps = 0.009$), and marginally higher compared to the 3-landmark condition ($M = 2.78$, $SD = 1.82$, $ps = 0.058$; see Fig. 3).

4 Discussion

The present study investigated whether increasing the number of landmarks shown on a mobile map leads to corresponding increases in navigators' cognitive load while they followed a given route in an urban virtual environment. Eye blink-related brain activity was analyzed to reveal cognitive load-dependent changes during map-assisted navigation. We hypothesized that the amplitudes of the P1 at the occipital region, N2 at the fronto-central region, and P3 at the parieto-occipital region would be more pronounced with increased number of landmarks displayed on the mobile map. Our hypothesis on the P3 amplitude was largely supported. It was significantly higher in the 7-landmark condition compared to the 5-landmark condition and marginally higher compared to the 3-landmark condition. However, there were no significant differences between the landmark conditions in the occipital P1 and front-central N2 amplitudes. The behavioral results show that landmark and route knowledge were significantly better in the 5- and 7-landmark condition compared to the 3-landmark condition [2].

The larger P3 amplitude in the 7-landmark condition suggests that participants were allocating more attentional resources to the task, indicating that presenting more landmarks on a mobile map adds to users' cognitive load. Future analysis could use statistical methods such as linear mixed models instead of ANOVAs to reduce inter-subject variance. When

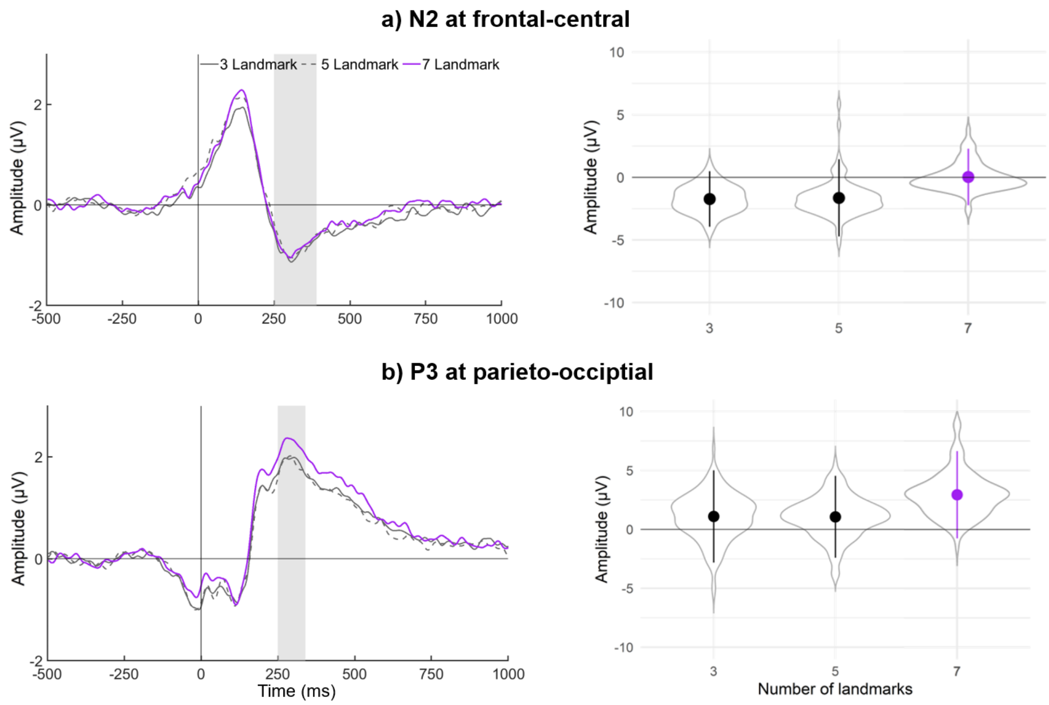

Figure 3 Left panel: Grand averaged amplitudes of bERPs for each landmark condition at the parieto-occipital region (Pz, POz, and Oz). The bERP waves served as visual inspection for individual peak detection – area shaded in gray indicates the time window where the P3 was extracted for each participant. Blink maximum occurred at 0 ms. Right panel: Violin plot displaying the means, standard deviations and distributions of the detected amplitude peaks in each landmark condition for the P3. Vertical lines denote 2× the standard deviation of the mean. Violin widths indicate the probability density of the data at different amplitudes.

considering the behavioral results, displaying five landmarks on the mobile map seems to have the best behavioral outcome without increasing cognitive load. On the other hand, displaying seven landmarks on the mobile map increased cognitive load without improving spatial learning performance [2].

Previous studies on blink-related N2 in the fronto-central region compared N2 amplitude during 1) rest, 2) physical activity, and 3) when performing a cognitive task. This comparison differs from that of the present study, which compared N2 amplitude at different levels of a cognitive task. It is possible that blink-related fronto-central N2 amplitude changes in load vs. no load conditions but is not sensitive to differing levels of cognitive load. This explanation needs further investigation.

5 Conclusion

Our current study provides initial evidence that presenting a greater number of landmarks on mobile maps increases users' cognitive load. Our preliminary results have several implications for the design of map-based navigation assistance systems and the literature on wayfinding. Our study shows that eye blink related potentials are sensitive to cognitive load changes in naturalistic settings. As most of the literature on ERPs use stimulus-evoked or response-related event markers, more research that investigates bERPs is needed. Moreover, designers of mobile maps should consider how the display could influence users' cognitive load during navigation. Specifically, the amount of information presented on mobile map displays should elicit an optimum level of cognitive load in users without taxing them beyond that used to perform an already cognitively demanding navigation task. The results of our study suggest that showing five landmarks on mobile maps could improve users' spatial learning performance without taxing extra cognitive resources.

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A EEG data preprocessing

The BeMoBIL pipeline 1.0 was used to preprocess and clean the EEG data using the MATLAB toolbox EEGLAB. We first downsampled the raw EEG data to 250 Hz. Then, we applied a 0.5 Hz high-pass filter to suppress slow drifts in EEG data and removed spectral peaks at 50 Hz, corresponding to power line frequency, using the *ZapLine* plus function. We identified noisy channels using the automated rejection function *cleanartifacts* from EEGLAB with ten iterations. We removed channels that were detected as bad channels more than four times and interpolated them by spherical interpolation of neighboring channels and applied re-referencing to the common average. On the cleaned dataset, we performed an independent component analysis (ICA) using an adaptive mixture independent component analysis (AMICA) algorithm. For each independent component (IC), we computed an equivalent current dipole (ECD) model with the DIPFIT plugin from EEGLAB.

B Analysis on number of eye blinks

The number of eye blinks did not differ by landmark density condition, $F(1, 44) = 1.49$, $p = .229$. Table 1 presents the average numbers of blinks per landmark density condition.

Table 1 Means and standard deviation (SD) of number of blinks in the three landmark density conditions.

	3-Landmark	5-Landmark	7-Landmark
Mean	143.98	130.04	138.87
SD	97	83.13	72.78