# Effect of cognitive load on spatial learning during navigation: a virtual reality study

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## 1 Introduction

GPS-enabled smart assistive devices are commonly used to facilitate navigation, especially in unfamiliar environments. When guided by such devices, turn-by-turn directions are at our fingertips in real time. However, increased use of mobile maps has been shown to negatively affect route and landmark learning. Considering the importance of spatial cognition in education and cognitive aging, and that millions of citizens navigate daily using navigation devices, there is a need to develop a navigation system that preserves spatial learning, while ensuring navigation efficiency.

Landmarks serve as cognitive anchors to structure an environment, and thus help navigators to determine their current location and heading in the environment and to get to a planned destination. Navigation and landmark learning are both mentally demanding tasks that may impact cognitive load and spatial learning. Level of task difficulty can be indicated by cognitive load measured by electroencephalography (EEG) (Gevins & Smith, 2003). Cognitive capacity theories suggest that learning performance drops when the number of learning items exceeds an individual's limited cognitive capacity (Luck & Vogel, 1997).

We thus hypothesize that 1) cognitive load, indicated by increased frontal theta and decreased parietal alpha activity, measured with EEG during a mobile map-assisted route-following task in a virtual environment will increase when the number of landmarks on the map increases, and that 2) spatial learning performance will improve with increasing number of landmarks on the map until this number exceeds the navigators' cognitive capacity, at which point spatial learning performance will decrease again.

## 2 Methods

We ran a power analysis for multilevel regression modeling prior to the experiment. Assuming a small to medium effect size (d = 0.3–0.5) for the within-person conditions with 17 trials each, a power analysis suggested recruiting 50 participants to achieve statistical powers of 73% for a small effect and 89% for a medium effect, respectively. Forty-eight adults (f=29, 18–35 yrs.) completed the study.

### 2.1 Stimuli and Apparatus

Three virtual cities were designed in ArcGIS CityEngine 2018.0 and displayed in a three-sided, stereoscopic cave automatic virtual environment (CAVE) using Unity 2018.4 LTS. Each city contained a route to be followed. Visually salient buildings at intersections were selected as landmarks to be shown on a map.

The route, including start and destination locations, was shown on a map projected in the center screen of the CAVE during navigation. This map rotated along with the participants' heading direction. It indicated participants' 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 landmarks were shown in 3D on the map, as seen in the environment. Experimental conditions varied landmark densities along the route on the map (within-subjects: three, five, and seven landmarks).

Participants' 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 impedances below 10 kΩ.

### 2.2 Procedure

Participants were asked to navigate as quickly as possible to a specific destination one of the three different cities and to learn the landmarks along the route that were displayed on the map. 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. The participants then repeated the procedure for the remaining two cities.

## 3 Analyses and results

### 3.1 Behavioral results

Multilevel regression modeling was conducted to compare spatial learning performance between the three landmark conditions in R 4.1.0. The result shows that landmark recognition and route direction memory improves when the number of presented landmarks increases from three to five, while learning performance does not increase further with seven landmarks depicted on the map, as hypothesized (Figure 1). There was no significant effect of the number of landmarks on JRDs.

### 3.2 EEG preprocessing

EEG data was preprocessed using a 1 HZ high pass and 100 Hz low pass filter with subsequent down sampling of the data to 250 Hz in EEGLAB v2021.0. Channels that contained artifacts were rejected using the *clean artifacts* toolbox and interpolated using spline interpolation. An independent component analysis (ICA) was performed using an adaptive mixture independent component (IC) analysis (AMICA) algorithm (Palmer et al., 2011). ICs were then localized in a standard head model using equivalent dipole modelling. After removing ICs reflecting eye movements, the data were back-projected to the sensor level for further data analyses in the time and frequency domains.

### 3.3 Time-frequency analysis

Event-related spectral was computed related to seventeen epochs of the map onset, with a time window of 0 to 4 seconds. Power of different frequency bands was calculated for central midline electrodes and tested for group differences using a linear regression model in R. Event latencies in wireless synchronization were corrected according to a projector (33 ms) and EEG trigger latency (100 ms). Relative power indices for each band (i.e., delta, theta, alpha, and beta) were computed as the percentage of the absolute power summed over the four frequency bands.

### 3.4 Time frequency results

We found that theta (4-8 Hz) synchronization in the frontal-central and parieto-occipital region increases when participants see seven landmarks compared to five and three landmarks (Figure 1), which only partly supports our hypothesis, and requires further analyses to fully understand the results. There is no significant effect of number of landmarks on alpha activity change in the parietal region. The behavioral and EEG results of the linear regression models are presented in Table 1.

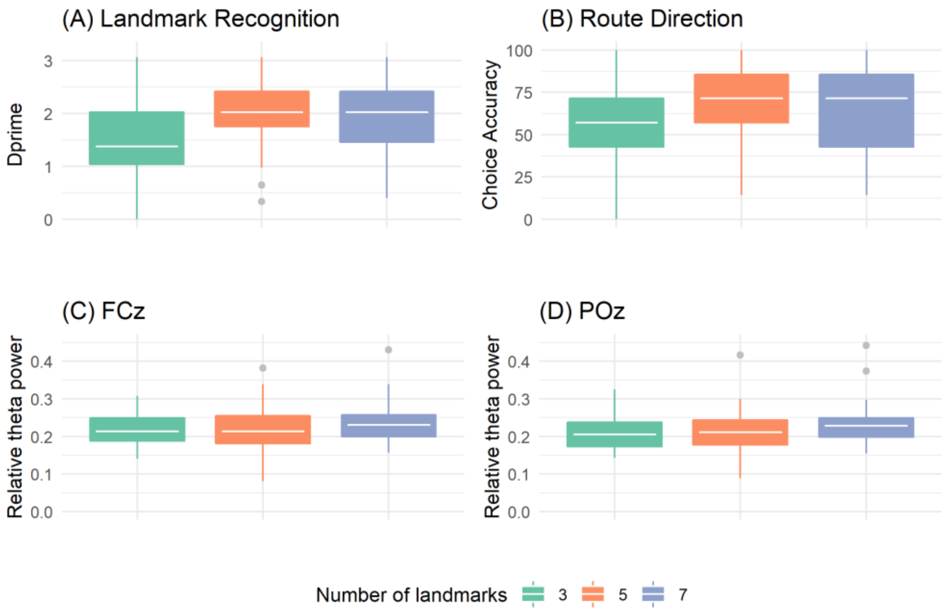


Figure 1: Spatial learning improves when more than three landmarks are shown (Plots A and B). Dprime in Plot A is calculated as the difference between the Z scores of the hit rate (recognition of seen landmarks) and that of the false alarm (recognition of not seen landmarks). Direction choice accuracy in Plot B are in percent. Theta synchronization increases at FCz and POz electrodes in the seven landmark condition (Plots C and D). [Grey dots represent outliers]

**Table 1**
Effect sizes (partial eta squared, $\eta_p 2$) and *p* values for the spatial learning performance differences and the relative theta power differences across three landmark conditions. Significant differences are in bold text.

| **Predictors** *(Number of Landmarks)* | **Landmark Recognition** $\eta_p 2$ | *p* | **Route Direction** $\eta_p 2$ | *p* | **FCz** $\eta_p 2$ | *p* | **POz** $\eta_p 2$ | *p* |
|---|---|---|---|---|---|---|---|---|
| 3 vs. 5 | 0.18 | **<0.001** | 0.10 | **0.001** | .004 | 0.546 | .001 | 0.799 |
| 3 vs. 7 | 0.13 | **<0.001** | 0.06 | **0.015** | .06 | **0.015** | .09 | **0.002** |
| 5 vs. 7 | 0.008 | 0.375 | 0.008 | 0.392 | .01 | 0.067 | .01 | **0.005** |

Random effect: $N_{subj} = 48$

## 4 Summary and outlook

This study aimed to improve the neuroergonomic understanding of the role of cognitive load in spatial learning during map-assisted navigation. Preliminary results suggest that the effectiveness of landmarks displayed on maps depends on their number and that the best performance is achieved with five landmarks with no additional cognitive load. We contend that mobile maps not only need to be designed to assist navigators to reach a destination swiftly and safely, but should also consider the wayfinders' spatial learning outcomes. The current study will inform the development of a neuroadaptive navigation system that optimizes pedestrians' environmental learning.

## References

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