**Title** Neural Mechanisms of Hierarchical Planning during Navigation

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Reinforcement Learning (RL) is a general framework for Machine Learning that also describes mammalian behaviour [1]. In order to allow decisions in complex environments, RL has been extended with the use of o*ptions* [2] that allow agents to learn the value of multicomponential sequences of actions in a given context [3, 4]. Options guide the agent to unique states designated as subgoals, at which a new option is selected. However, although prediction error signals for interim goals have been observed in the striatum [5], it remains unknown whether unique representations of subgoal states exist in the human brain.

To address this question, we used fMRI to measure BOLD signal of 20 healthy participants (10 female; age 19-34, mean 25.6 years) who performed a navigation task within a virtual environment representing a subway network. We predicted that stations where the lines intersected (exchange stations) would be treated as subgoals and would garner unique behavioural and neural effects. During a training session, participants became familiar with the environment by repeatedly completing journeys within the same network. Once they reached the destination station, participants received feedback on the duration of their journey (and the optimal duration). During training only, participants could see a map of the network, and were quizzed about it to ensure that they were learning. On a subsequent day, participants undertook a second session whilst undergoing whole-brain fMRI. In the scanner they also completed multiple journeys but no feedback was given. A reward-based system was put in place, such that each journey had a fixed probability of being cancelled. Participants earned bonus income by reaching their goal on time, and thus tried to minimise the absolute distance of their paths. Around 50% of the journeys were cancelled for each participant.

We found an increase in reaction times as subjects approached a line change, which quickly returned to baseline-level afterwards. Critically, this observed pattern depended on the subjects’ actual line-change at that station.

On the neural level, we revealed higher activation in the dorsolateral prefrontal cortex when an exchange station was reached, which was independent of a line change. This suggests a higher cognitive load at exchange stations in general. An increase of activation in the postcentral gyrus was observed for a change in direction (switch of response), irrespective of the station being an exchange station or not.

Specifically for line-changes, i.e. when the response was changed *and* it was an exchange station, we found higher activation in a network of right caudate nucleus, thalamus, and the supplementary motor area. This provides evidence that the striatum indeed also signals for the reach of subgoals. These activations persisted even when we controlled for the response switch from the previous trial, ensuring that the observed effects were not mainly driven by a switch of the motoric response (???).

Meanwhile, medial Prefrontal Cortex (mPFC) correlated (negatively) with the distance to final destination, underlining its proposed role in XXX.

This results provide evidence that a unique network is activated when participants reach an interim goal during navigation. Our findings suggest that humans represent the value of actions in a hierarchical fashion, and that the interconnected structures signal when a subgoal has been reached.

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