**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. For example, when moving around a building, agents may learn the value of reaching a doorway to enter a new room. 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) performed a navigation task within a virtual environment representing a subway network. Each network consisted of multiple stations identified by unambiguous names and connected via "subway lines" represented with a distinct colour. 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 repetedly completing journeys within the same network. They executed their plan using cardinal directions (*north*, *south*, *west*, *east*) and an additional action (*switch*) to change between lines at an exchange station. Finally, once they reached the destination station, participants received feedback on the duration of their journey (and the optimal distance). 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 the colour of the lines were removed and no additional action was required to switch between lines. 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.

Reaction times increased as the subject approached a line change, and became lower than average directly after the change. Critically, this did not happen around exchange stations where the subject did not change lines.

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, suggestive of a higher cognitive load. An increase of activation in the postcentral gyrus was observed for a change of direction (i.e. response) from the previous trial, independently of being in 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 signals for the reach of subgoals. Meanwhile, acitivty in medial Prefrontal Cortex (mPFC) increased as subjects approached the final destination, underlining its role in tracking value.

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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