How do humans learn concepts and strategies?

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Abstract

Concepts and strategies have traditionally been the focus of two separate fields of study: one studying the computations underlying representation learning (Behrens et al., 2018) and the other studying the mechanisms underlying planning (Callaway, Hardy, & Griffiths, 2022). But how does the acquisition of concepts depend on their application in strategies? Here, we investigated this question by comparing two training curricula in a grid world game where, to succeed, human participants had to learn new concepts and apply those concepts in strategies. During training, different groups of players experienced the same game rounds in one of two different orders (training curricula): a curriculum prioritising the application of new concepts at a shallow planning depth (concept-first) and a curriculum prioritising applying a single concept in increasingly complex strategies (strategy-first). We found that learning was promoted by the strategy-first curriculum.

Keywords: concepts; strategies; planning; curriculum learning

Concepts are the fundamental building blocks of human knowledge: they make up our internal models of the world and inform our inferences, choices and actions. Whilst recent work has shed light on how humans learn and organise new conceptual knowledge (Behrens et al., 2018; Bellmund, Gärdenfors, Moser, & Doeller, 2018), we do not know how successful learning trades off the need to both acquire conceptual knowledge and practice deploying it for problem-solving.

Here, we asked human participants (n=101) to play a grid world game inspired by an escape room (Figure 1a). Players navigated an avatar through a series of rooms using tools (game concepts) whose function was not visually signalled (and had to be learned by trial and error). For instance, a catapult could propel the avatar over a wall if approached from the correct direction.

To solve the task, players had to chain the concepts together in an escape strategy of given depth (Figure 1b). Thus, game problems featured different levels of complexity along two axes: conceptual complexity (number of concepts needed to solve the problem) and strategic complexity (planning depth, Figure 2a-b). In a between-group design, we compared curricula in which (1) participants learn first about concepts under shallow planning depth (concept-first condition); or (2) learn to plan deeply with a single concept (strategy-first

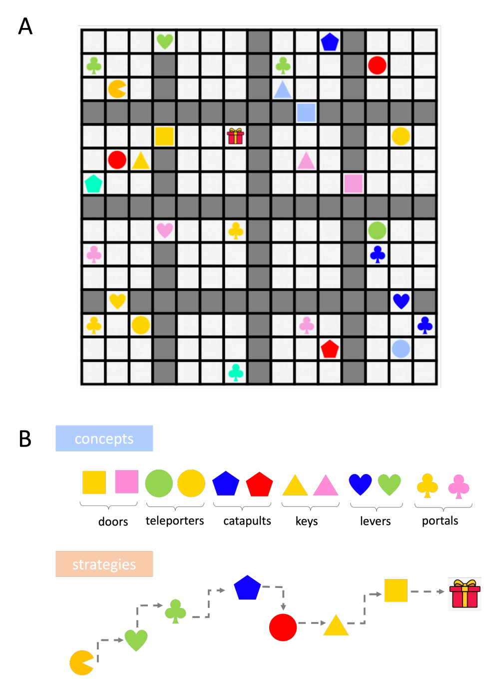

Figure 1: A. Game screenshot. The player moves the yellow sector shape (avatar). B. Illustration of concepts and strategies in the game. The player needs to learn what is there in the game (concepts) and apply this knowledge in making a plan (strategies) to reach the goal (red present).

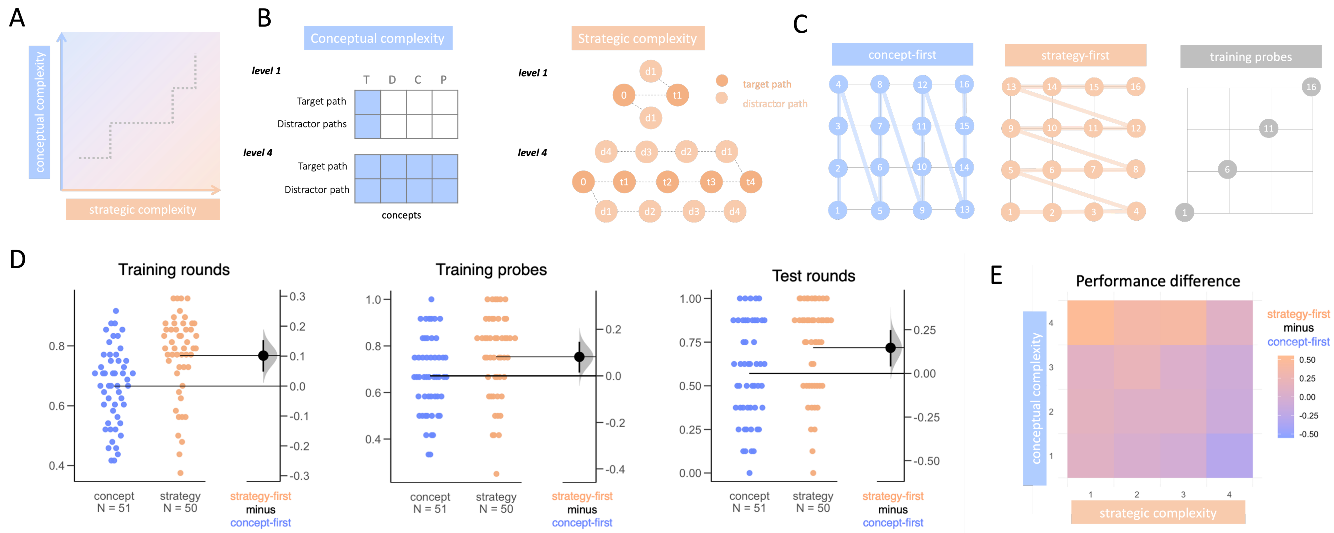

Figure 2: A. A schematic of the 2-dimensional complexity space. Dotted line illustrates one trajectory through the space. B. Manipulations of conceptual and strategic complexity. Left: In conceptual complexity level 1, the game layout contains only one game concept – here, teleporters (blue cell in the table); in conceptual complexity level 4, the game layout features 4 different concepts. Right: In strategic complexity level 1, the target path (dark orange circles) features only one transition between rooms – from the spawn room (0) to the goal room (t1). Similarly, distractor paths (paler orange) also feature just one transition. In strategic complexity level 4, the target and distractor paths all feature 4 transitions between rooms. C. Training curricula. Both training curricula spanned the same 16 complexity levels (nodes). The numbers correspond to the presentation order of each level in the concept-first (blue) and strategy-first curricula (orange). The presentation order for 4 of the levels (grey) coincided for the two curricula. D. Performance plots. Each data point corresponds to a single participant, the color corresponds to the curriculum condition. The y-axis tracks the fraction of successfully solved game rounds (left) and the difference between the two conditions (right). The 95% bootstrap confidence interval for the mean difference (black line) was calculated using the package dabest (J. Ho et al., 2019). E. Difference in average performance between participants in the strategy-first and concept-first curriculum across the 16 complexity levels. Orange indicates strategy-first>concept-first, blue - vice-versa.

condition).

Players completed 48 procedurally generated training rounds of varying complexity, ordered according to the curriculum condition (Figure 2c). There were 4 levels of conceptual complexity and 4 levels of strategic complexity, totalling 16 distinct game levels. Both curricula comprised the same game levels presented in different order. Crucially, the timing of game levels $\{1, 6, 11, 16\}$ coincides so we could directly compare players' performance on those levels (training probes, grey). Each player completed 3 rounds per level during training, and then 8 test rounds at the highest complexity level following training.

We calculated performance as the percentage of game rounds solved successfully by each participant. Figure 2d visualises the results. Performance was higher in the strategy-first curriculum across all training rounds (Permutation Two Sample t-test (Monte Carlo) $p < 0.001$), training probe rounds ($p = 0.02$) and test rounds ($p < 0.01$). During training, participants in the strategy-first curriculum performed better across 12/16 training levels, and particularly so in levels of high conceptual complexity (Figure 2e). Our results suggest that allowing participants the opportunity to practise new concepts through applying them in strategies promotes learning.

But why does applying concepts in strategies of increasing planning depth facilitate concept acquisition? Recent work has demonstrated that internal representations can be flexibly reconfigured according to their relevance to participants' plans (M. K. Ho et al., 2022) and behaviour (Park, Leahey, & Funk, 2023). This flexible reconfiguration may simplify representations by warping or dropping irrelevant information. The strategies-first curriculum may encourage the acquisition of rich conceptual knowledge by highlighting the task-relevance of to-be-learned concepts.

The finding that privileging planning depth promotes learning sits nicely with classic ideas in cognitive science that processing depth affects how well new information is remembered (Craik & Lockhart, 1972). Within the levels-of-processing framework, engaging with the information in more elaborate ways (e.g. here, applying it in more complex strategies) leads to a more enduring representation. And so, in applied settings, learners benefit from "desirable difficulties" during learning such as attempting to recall information rather than repeatedly rereading it (Bjork & Bjork, 2011). This principle guides active learning pedagogies in education practice (Yannier et al., 2021). Our work contributes a basic science perspective to this interdisciplinary body of knowledge.

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