

# IQ and working memory predict plan-based sequential action learning

**Roy de Kleijn (kleijnrde@fsw.leidenuniv.nl)**

Cognitive Psychology Unit, Leiden University  
Leiden Institute for Brain and Cognition

**George Kachergis (george.kachergis@gmail.com)**

Department of Artificial Intelligence, Radboud University, Nijmegen  
Donders Institute for Brain, Cognition and Behavior, Nijmegen

**Bernhard Hommel (hommel@fsw.leidenuniv.nl)**

Cognitive Psychology Unit, Leiden University  
Leiden Institute for Brain and Cognition

## Abstract

How people learn and produce sequential actions (e.g., making coffee) has been the subject of intense empirical and theoretical scrutiny, for it covers most human activities. One useful distinction is between stimulus-based control, in which action selection is driven largely by the environment, and plan-based control, which assumes learning of structured sequences of actions and effects. Task demands and instructions can modulate which control mode is used, as well as participants' individual abilities and inclinations. Here we investigate two mouse-based sequence learning tasks, with one key difference: in the cued task, either control mode is possible, while learning in the reinforcement task requires plan-based control. Using measures of visuospatial working memory (VWM) capacity, locus of control, need for structure, and IQ, we seek to identify and explain individual differences choice of control mode and task performance, establishing a link between VWM capacity and performance, as well as explicit knowledge evidencing plan-based control.

**Keywords:** sequential action learning; reinforcement learning; individual differences; trajectory serial response time task

## Introduction

Nearly all everyday actions can be considered sequential: from making coffee to using the bathroom, these complex actions consist of subactions that are completed one after another. Decades of research have been dedicated to uncovering the mechanisms enabling us to learn and execute such action sequences. An early theory by James (1890) argued that elementary action units in a sequence are triggered by the sensory effects of the preceding unit. However, Münsterberg (1892) noted that such an associative account is insufficient to explain sequential action because a directional element is required to successfully execute subactions in the correct order. Instead, he argued that the learning of action sequences relies on the acquisition of a motor program. More recently, it has been suggested that these two approaches are not mutually exclusive, but in fact reflect two different executive control modes that—under specific circumstances—can be strategically chosen (Tubau, Hommel, & López-Moliner, 2007).

### Stimulus-based and plan-based control

Tubau et al. (2007) compared James' stimulus-driven account of sequential action with the *prepared reflex* concept of Hommel (2000), and referred to it as *stimulus-based control*. This type of executive control is characterized by the

automaticity by which stimuli are attended to. Due to the highly automatized response to stimuli, the sequence itself is often not learned. Instead, what is learned is a strategy of delegating control to external stimuli (Tubau et al., 2007). In other words, people learn how to respond quickly to incoming information. *Plan-based control*, on the other hand, is assumed to rely on action plans, which are structured sequences of action effects (Miller, Galanter, & Pribram, 1960; Hommel, 2003). In contrast to stimulus-based control, representations in plan-based control are *internally* generated. There is evidence to suggest that sequence learning does not rely on the prediction of sequences of external stimuli, but the prediction of the motor action to be performed. In other words, participants do not learn stimulus-event sequences, but in fact learn sequences of *responses*. As such, it is thought that sequence learning involves a shift from stimulus-based control to plan-based control, implying the generation of action plans by which participants can predict a sequence of responses even in the absence of stimuli (Hoffmann & Koch, 1997; Nattekemper & Prinz, 1997).

Tubau et al. (2007) investigated this shift and its modulators in a comprehensive study consisting of five experiments. In a serial reaction time paradigm in which participants had to respond to the letter X appearing on the left or right side of the screen and responding with the appropriate hand, they presented participants with a repeating sequence of stimuli. In this sequence, location switches occurred four times more often than location repetitions, but stimuli were equally often presented to the left or right. They found that participants' control mode was influenced by instruction type, where intentional instruction (i.e. telling participants that the shown sequence is deterministic, and is to be learned explicitly) induced plan-based control. Participants' control mode was assessed by the size of the frequency effect, which should be smaller under plan-based control. Participants who received intentional instructions showed a smaller frequency effect, which was attributed to the formation of an action plan. These participants were more likely to acquire explicit knowledge of the sequence, as they were able to verbally report the correct

sequence at the end of the experiment<sup>1</sup>.

However, plan-based control is not just a strategy that participants employ at their own choosing—task structure and demands have a large influence. For example, removing stimulus-response compatibility by using symbolic stimuli instead of spatially-compatible stimuli seems to lead to plan-based control, as is evidenced by the elimination of the frequency effect. Also, playing irrelevant sounds that hamper symbolic encoding of the sequence prevents the successful formation of an action plan, leaving stimulus-based control the only viable mode of executive control (Tubau et al., 2007). In some circumstances, stimulus-based control is not a feasible strategy due to the lack of stimuli. This will be the case in the exploratory sequence learning task used in this study.

### Studying sequence learning

The acquisition of sequences has been the subject of study in domains ranging from linguistics (Elman, 1990; Saffran, Newport, & Aslin, 1996; Reber, 1967) to everyday action (Botvinick & Plaut, 2004; Cooper & Shallice, 2000), with perhaps the *serial response time task* (SRT) being the most popular paradigm (Nissen & Bullemer, 1987).

In the SRT task, a visual stimulus appears in one of four locations, horizontally arrayed on a computer screen. Four buttons are located below the four possible stimulus locations, and participants are asked to quickly press the button when the corresponding visual stimulus appears. In their original study, Nissen and Bullemer (1987) compared a condition using random stimulus locations with a condition using a repeating, deterministic sequence, and found evidence for implicit sequence learning: participants in the deterministic sequence showed larger reduction in response times than participants in the random condition.

Most of the sequence learning literature has focused on cued paradigms such as the SRT task, in which participants have to respond to sequences of stimuli that appear. However, sequence learning in daily life is often not learned by simply chaining stimulus-response associations (Lashley, 1951). Instead, acquiring new action sequences is better characterized as *exploratory*, in which people try several alternatives before discovering the correct one.

A recent study adapted the SRT task to a reinforcement learning paradigm (Kachergis, Berends, de Kleijn, & Hommel, 2016). In this task, participants were not *cued* by the stimuli, but had to *explore* the four alternatives to find out which one was correct. Participants could collect points by predicting the next stimulus correctly. A strong correlation was observed between behavior on the SRT task and its reinforcement learning adaptation in terms of response time and accuracy per sequence position. Interestingly, the final scores were bimodally distributed, suggesting that participants used different strategies. Although purely stimulus-based control is impossible in this paradigm, it is clear that the accuracy of

participants' action plans showed a large range of variance. Although their study investigated both the SRT task and its reinforcement learning adaptation, the study had a between-subject design, making it impossible to examine characteristics of participants that produce effects that are common to both tasks.

### The current study

In scenarios where both stimulus-based control and plan-based control are possible, participants may strategically (or perhaps even randomly) choose an executive control mode. In the current study, we investigated predictors of executive control mode in an SRT task and action plan formation in a reinforcement learning task in which plan-based control is the only control mode available.

Earlier research has shown that visuospatial working memory capacity predicts both implicit and explicit sequence learning performance (Bo & Seidler, 2009; Bo, Jennett, & Seidler, 2011). In this study, we will look at visuospatial working memory capacity and IQ measurements as predictors of executive control mode that reflect cognitive limitations. One possibility would be that some participants simply do not have the cognitive capacity to form (long enough) action plans. Another possibility would be that control modes are chosen strategically or preferentially. The formation of an action plan might reflect individual differences in the need for structure. That is, some people may prefer to actively predict the future according to a plan or schema instead of waiting for stimuli to arrive, while others might want to delegate control to the external environment (Neuberg & Newsom, 1993).

## Method

### Participants

Forty undergraduate and graduate students (13 males, 27 females) were recruited from Leiden University. Participants either received course credit or were paid 6.50 EUR for participation. All participants had normal or corrected-to-normal vision. The total duration of the experiment was 90 minutes.

### Materials

In order to assess possible predictors of participant behavior, several tasks and questionnaires were administered.

**Fluid intelligence** Fluid intelligence was estimated using a shortened, 10-minute version of the Raven's Standard Progressive Matrices (SPM) test (Raven, Raven, & Court, 1998). It measures the individual's ability to form perceptual relations and for analogical reasoning. It is a widely used test to measure fluid intelligence, independent of language and schooling, and is considered to have excellent reliability (Burke & Bingham, 1969). The number of correct responses in 10 minutes over all participants are normalized to a distribution with mean 100 and SD 15, resulting in an estimated IQ score.

<sup>1</sup>Although it should be noted that explicit sequence knowledge is not necessary for learning (see e.g. Lewicki, Hill, & Bizot, 1988; Nissen & Bullemer, 1987).

**Personal need for structure** To assess participants' tendency to seek out structured ways of dealing with the world, we administered the Personal Need for Structure scale (Thompson, Naccarato, & Parker, 1989). This questionnaire quantifies people's need for simple structure, and consists of 12 statements (e.g. "I enjoy having a clear and structured mode of life.") which the participant can either agree or disagree with, rated on a 6-point scale. It has been shown to have good reliability and validity (Neuberg & Newsom, 1993). It has been hypothesized that personal need for structure reflects a strategy for simplifying the world due to a general lack of intellectual abilities, but the correlation between the PNS scale and IQ seems to be minimal (Neuberg & Newsom, 1993). It is therefore more likely to reflect a strategy that participants can choose to employ, and participants who score high on this measure could be more likely to actively search for structure in action sequences.

**Visuospatial working memory** We assessed visuospatial working memory using the computer task from Bo et al. (2011). In their study, which used an adaptation of the visual working memory task used by Luck and Vogel (1997), a relationship was found between visuospatial working memory capacity and performance on a serial reaction time task. In this task, participants were presented with a sample array for 100 ms followed by a blank screen delay of 900 ms, after which a test array was presented for 2000 ms. Participants were asked to determine whether the test array was different or similar to the sample array by pressing either D or S. Arrays consisted of 2–8 colored circles, and for each trial the test array was either the same as the sample array or different with one of the colors changed. Visuospatial working memory capacity was calculated as  $K = \text{array size} (\text{hit rate} - \text{false alarm rate})$ . The average  $K$  across all array sizes was computed to estimate visuospatial working memory capacity (Bo et al., 2011). Participants completed 140 trials in total.

**Trajectory SRT task** The trajectory SRT task is an adaptation of the serial response time task introduced by Nissen and Bullemer (1987). It maps the four buttons of the original SRT task to four squares located on the corners of a computer screen, requiring participants to move the mouse cursor to each square that lights up (Kachergis, Berends, de Kleijn, & Hommel, 2014a, 2014b). Unbeknownst to participants, the sequence is a repeating sequence of 10 items. Speed-up over time compared to a condition with a random sequence is thought to reflect implicit learning of the sequence. In the current study, we used a different sequence (3-2-4-2-1-4-3-4-2-1) than in the original SRT task to prevent carryover effects between this task and the RL task. The complete task consisted of 800 movements (80 repetitions of the 10-item sequence). In order to assess first-order frequency effects, the sequence was designed in such a way that it consisted of 8 straight movements, and 2 diagonal movements. After completing the 800 movements, participants were asked if they noticed any structure within the experiment, and if so, were

asked to reproduce the sequence.

**Reinforcement learning task** The RL task is an adaptation of the trajectory SRT task (see above), with the difference being that the next stimulus is not cued, but to be discovered by the participant through trial-and-error (Kachergis et al., 2016). Participants moved to one of the four squares, and received feedback by the square turning green in the case of a correct movement, and being returned to the center of the screen in the case of an incorrect movement. Points were awarded for correct movements (+1 point), and deducted for incorrect movements (-1 point), and participants were instructed to maximize their amount of points. The amount of points collected was continuously visible to the participant, their progress in the task, however, was not. The task ended after 800 correct movements of the original SRT sequence (4-2-3-1-3-2-4-3-2-1). A participant having knowledge of the sequence before starting and who never made a mistake would therefore make 800 movements directly to valid targets, receiving a theoretical maximum score of 800 points. A participant with no memory of even the previous target they had tried could make an infinite number of mistakes, never finishing the experiment. If participants would not repeat the same invalid target more than once when seeking each target (i.e. an elimination strategy), a participant would expect on average to score 0 points, as the expected value of completing one movement successfully is 0 using this strategy<sup>2</sup>. Participants were not told that there was a repeating deterministic sequence, let alone details such as how long the sequence was.

## Design and procedure

All participants performed both the trajectory SRT task, as well as the reinforcement learning task. The order of the two tasks was counterbalanced over participants, and the two tasks used different sequences to prevent carryover effects.

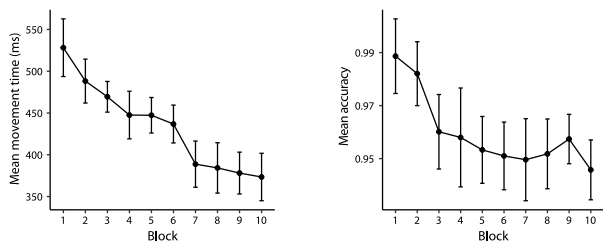
Participants were seated at a computer after having given their informed consent. All subsequent tasks were performed on the computer. First, the Personal Need for Structure questionnaire was completed, followed by the visuospatial working memory task, and Raven's SPM. After this, participants were given a 5-minute break. Participants then completed, in counterbalanced order, the trajectory SRT task and the reinforcement learning task.

## Results

### Trajectory SRT task

Prior to analysis, movement times > 1500 ms were removed, and the experiment was divided into 10 blocks of 8 sequence repetitions. As an analysis of data collected earlier using a random sequence showed no significant difference in movement times between straight and diagonal movements, there was no correction applied for the somewhat larger distance required to make diagonal movements.

<sup>2</sup>33% chance of success in one try (+1), 33% chance of success in two tries (-1+1), and 33% chance of success in three tries (-1-1+1).



(a) Participants' movement time decreased over time, indicating learning of the sequence.

(b) Error rates increased during the first three blocks, but remained relatively stable during the rest of the task.

Figure 1: Movement times and accuracy for the trajectory SRT task. Error bars indicate 95% CI.

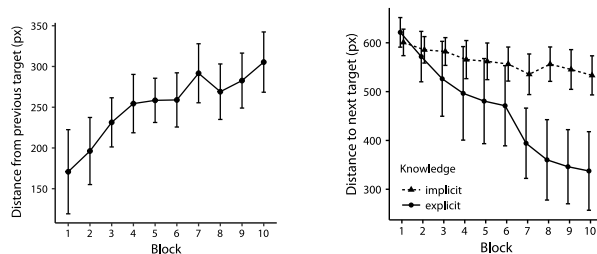
**Response times** Comparative analyses were performed using the means of participants' median movement time, with the movement time defined as the time between cue onset (stimulus changing color) to touching any part of the stimulus with the mouse cursor. Median movement time to a target was 464 ms ( $SD = 223$  ms). Participants' movement time decreased from 546 ms in the first block to 413 ms in the tenth block, indicating learning of the sequence,  $F(9, 360) = 15.80$ ,  $p < .001$ ,  $\eta_G^2 = .126$ . Accuracy was high across all blocks of the experiment, but especially so during the first two blocks. There was an effect of time on accuracy,  $F(9, 360) = 4.50$ ,  $p < .001$ ,  $\eta_G^2 = .042$ , indicating some degree of speed-accuracy tradeoff. However, after the third block movement times are still decreasing, while accuracy remains stable. Both movement times and accuracy are shown in Figure 1.

**Explicit sequence knowledge** Participants were grouped into an implicit knowledge group and an explicit knowledge group. Only those 13 participants who could correctly recall the complete repeating sequence after having completed the task were considered to have explicit knowledge. Participants with explicit sequence knowledge had a significantly larger working memory capacity (2.87 vs. 2.25,  $t(28.08) = 2.95$ ,  $p = .006$ ,  $d = 1.11$ ), but did not differ on estimated IQ or Personal Need for Structure scales ( $t_s < .81$ ,  $p_s > .42$ ).

**Modes of executive control** Similar to Tubau et al. (2007), we used frequency effects (i.e. the facilitation of responses to frequent (straight) compared to infrequent (diagonal) transitions) to determine whether participants engaged in either stimulus-based or plan-based control. An analysis of variance revealed main effects of block, frequency, and knowledge on movement time (see Table 1). Overall, participants with explicit sequence knowledge had faster movement times ( $M = 398$  ms) than participants without ( $M = 485$  ms), and frequent (straight) movements were performed faster ( $M = 417$  ms) than infrequent (diagonal) movements ( $M = 496$  ms).

Factor	$df$	$F$	$\eta_G^2$	$p$
Block	9, 342	23.94	.17	< .001
Block $\times$ Knowledge	9, 342	8.37	.07	< .001
Frequency	1, 38	106.00	.09	< .001
Frequency $\times$ Knowledge	1, 38	4.43	.004	.042
Frequency $\times$ Block	9, 342	2.75	.005	.004
Knowledge	1, 38	6.44	.089	.015

Table 1: Results of analysis of variance on movement times.



(a) Participants made increasingly larger movements during the ITI.

(b) Initial distance to the stimulus decreased over time, reflecting correct prediction of the next stimulus.

Figure 2: Predictive movements in the trajectory SRT task. Participants made increasingly larger predictive movements, which reflects correct prediction of the next stimulus. This effect was stronger for explicit than for implicit learners. Error bars indicate 95% CI.

**Predictive movements** As the task progressed, participants made an increasing amount of movement during the ITI—in the absence of a stimulus,  $F(9, 342) = 6.53$ ,  $p < .001$ ,  $\eta_G^2 = .053$ . Total ITI (predictive) movement, defined as the distance from the previous target at the onset of the next target, increased from 171 pixels in block 1 to 305 pixels in block 10. There was no main effect of knowledge. Results are shown in Figure 2a. Similar to Dale, Duran, and Morehead (2012), we define *correct* predictive movement as the distance to the next target at target onset. An analysis of variance using block and knowledge as factors shows a main effect of block, meaning that distance to next target decreased from 609 pixels to 474 pixels, or that correct predictive movement increased over time,  $F(9, 342) = 32.36$ ,  $p < .001$ ,  $\eta_G^2 = .22$ .

In the final block of the task, predictive movements (defined as movements  $> 300$  pixels during the ITI, but not necessarily toward the correct target) appeared to show a mixed distribution over participants. Where some participants hardly showed any movement during the ITI, others had almost half of all their movements classified as predictive. Hartigan's dip test of unimodality (Hartigan & Hartigan, 1985) confirms this observation,  $D = .079$ ,  $p = .038$ .

While implicit learners hardly increased their correct predictive movements, explicit learners showed a strong increase over time, as evidenced by a block  $\times$  knowledge interaction,

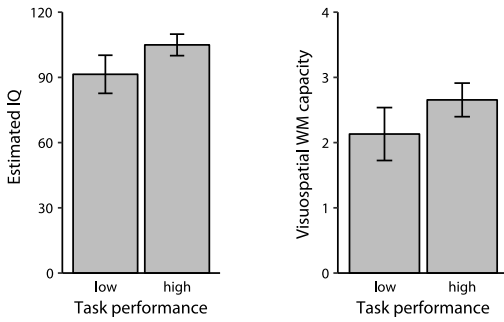


Figure 3: Differences in estimated IQ and visuospatial working memory capacity between low and high performers on the reinforcement learning task. Error bars indicate 95% CI.

$F(9, 342) = 14.00, p < .001, \eta_G^2 = .11$ . Results are shown in Figure 2b.

### Reinforcement learning task

Maximum score on the reinforcement learning task was 800, with the most basic elimination strategy leading to 0 points. Mean score was 525, ranging from 140 to 774 points. Distributions of scores was non-normal, with a large group of participants scoring around 700 points, and a group scoring quite low. For subsequent analyses, a midpoint split on 457 points was performed, dividing the participants into low and high performers.

**Predicting task performance** Low performers on the reinforcement learning task had a significantly lower estimated IQ of 91.4, compared to high performers with an estimated IQ of 104.9,  $t(39) = 3.06, p = .004, d = .98$ . Also, low performers had a significantly lower visuospatial working memory capacity of 2.13 vs. the high performers' 2.65 capacity,  $t(39) = 2.40, p = .021, d = .77$ . Results are shown in Figure 3. IQ and visuospatial working memory capacity were uncorrelated,  $r(39) = .213, p = .181$ .

There was no difference between the two groups on the Personal Need for Structure scale,  $t(39) = .28, p = .780$ . Explicit sequence knowledge was strongly related to task performance, as the 23 participants with explicit sequence knowledge had a far higher final score ( $M = 634$ ) than participants without explicit knowledge ( $M = 375$ ),  $t(24.67) = 4.61, p < .001, d = 1.86$ .

**Stimulus- vs. plan-based control** In the SRT task, two measures of executive control mode are used. First, explicit knowledge of the sequence is considered to be an indicator of a plan-based control mode, similar to Tubau et al. (2007). Second, the amount of correct predictive movements is evidence of the existence of an action plan, implying a plan-based control mode. Participants with explicit sequence knowledge in the SRT task were more likely to have acquired explicit sequence knowledge in the reinforcement learning

task, McNemar's  $\chi^2(1, N = 40) = 4.5, p = .034$ . This suggests that the acquisition of explicit knowledge in both tasks relies on a common mechanism or dependency. However, the amount of correct predictive movements in the SRT task was not related to the final score in the reinforcement learning task,  $r(38) = .025, p = .880$ , nor did explicit knowledge in the reinforcement learning task relate to correct predictive movements in the SRT task,  $t(38) = 1.32, p = .195$ .

In summary, participants using plan-based control in the SRT task did not score higher on the reinforcement learning task, but participants with explicit knowledge formation in the SRT task were more likely to acquire explicit knowledge on the RL task. This suggests that predictive movements and explicit knowledge do not similarly reflect successful plan formation, and may not be equally good indicators for a plan-based control mode.

### Discussion

Learning was evident in both the trajectory SRT task and the reinforcement learning task. In the trajectory SRT task, the findings of Tubau et al. (2007) were replicated. The trajectory paradigm allowed us to find further evidence for a plan-based mode of control: participants made increasingly large movements toward the next stimulus, but participants with explicit knowledge of the sequence did more so than those with implicit knowledge. Instead, participants without explicit knowledge tended to re-center the mouse during the ITI, moving to a position equidistant to all stimuli.

In the reinforcement learning task, final scores showed a bimodal distribution, similar to what has been reported in Kachergis et al. (2016). The low-performing and high-performing groups differed in IQ and working memory capacity, but did not differ in personal need for structure or locus of control. This suggests that sequence learning in an exploratory paradigm is not determined by personal characteristics or preferences, but by cognitive limitations.

In both the SRT task and the reinforcement learning task, explicit sequence knowledge was predicted by visuospatial working memory capacity. Earlier research by Bo et al. (2011) showed a relationship between visuospatial working memory capacity and performance on a non-trajectory SRT task, but the current study shows that this holds in an exploratory paradigm as well and predicts explicit sequence knowledge. The observation that participants who were more likely to acquire explicit sequence knowledge in the SRT task were also more likely to acquire it in the reinforcement learning task further corroborates this finding.

A promising approach to investigating this relationship is by modeling the learning process in the reinforcement learning task. IQ and visuospatial working memory could be compared to the learning rate and state space in reinforcement learning models that are fit to the performance of individual participants. This may shed further light on the exact mechanisms that explain the wide range of performance on exploratory sequence learning.

Another possible explanation of the diverse learning outcomes could be rooted in different beliefs about the task. Participants were not told that the response locations would be a repeating, deterministic sequence. They may have instead believed it was to some extent probabilistic—as many psychological tasks are. Different assumptions about the task may lead participants to arrive at different strategies, with variable success in the task. Participants expecting a random sequence may be less inclined to predict the next stimulus and are—in the current paradigm—indistinguishable from participants expecting a deterministic sequence but unable to learn it due to intellectual limitations. However, manipulating these variables is straightforward and could be an interesting avenue for future research.

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