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Does the Acquisition of Spatial Skill Involve a Shift From Algorithm to Memory Retrieval?

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Performance on verbal and mathematical tasks is enhanced when participants shift from using algorithms to retrieving information directly from memory (Siegler, 1988a). However, it is unknown whether a shift to retrieval is involved in dynamic spatial skill acquisition. For example, do athletes mentally extrapolate the trajectory of the ball, or do they retrieve the future location from memory? To examine this question, 2 experiments were conducted using a task paradigm similar to the game Pong—a ball was launched from 1 side of the screen and participants attempted to position a paddle to intercept the ball. In Experiment 1, participants responded to a limited number of repeated trajectories. During the learning phase, the response deadline was near the paddle. During the difficult phase, the response deadline was closer to the launch point. During the critical phase, novel trajectories were introduced at the difficult response deadline. If participants are using a retrieval strategy by the critical phase, performance should be significantly worse on the novel trajectories, whereas if they are using an algorithmic strategy, performance on the novel trials should be similar to performance on the repeated trajectories. In Experiment 2, half the participants followed an experimental paradigm similar to Experiment 1 and half experienced all novel trajectories throughout the task. Our results were consistent with a shift from algorithmic processing to retrieval—participants performed significantly better on repeated trajectories relative to novel trajectories. Furthermore, retrieval strategies enhance performance above and beyond what is gained by practicing the algorithm alone.

Keywords: skill acquisition, strategy, spatial, retrieval, interception

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With practice, performance on a given task typically improves from one of high effort, inefficiency, and frequent errors, to error-free and relatively efficient, to effortless and automatic. Fitts and Posner (1967) referred to these as the cognitive, associative, and autonomous stages, respectively. These three stages of learning have been supported in a number of psychomotor tasks, including sending telegrams in Morse code (Bryan & Harter, 1899; Keller, 1958), rolling cigars (Crossman, 1959), and novel laboratory motor tasks (e.g., Puttemans, Wenderoth, & Swinnen, 2005; Wulf, McNevin, & Shea, 2001). Similar two- and three-stage models have been supported in cognitive skill acquisition tasks including reading (Rawson & Middleton, 2009; Siegler, 1988a), mental arithmetic (Delaney, Reder, Staszewski, & Ritter, 1998; Reder & Ritter, 1992; Rickard, 1997; Siegler, 1988a, 1988b; Tenison & Anderson, 2016; Wilkins & Rawson, 2010), and visual search tasks (Ackerman & Cianciolo, 2002; Ackerman & Woltz, 1994; Wilkins & Rawson, 2010). With each successive stage, errors and completion times decrease.

Changes in cognitive strategies underlie the three stages of cognitive skill acquisition (Anderson, Matessa, & Lebiere, 1997; Haider & Frensch, 1996; Logan, 1988; Rickard, 1997). Consider Anderson's Act-R model of cognitive skill acquisition (Anderson et al., 1997; Tenison & Anderson, 2016): During the cognitive stage, people rely on inefficient algorithms, such as sounding out words when reading or counting to solve basic arithmetic problems. With practice, people enter the associative stage where there is a shift from algorithmic processing to an effortful search through memory for the correct response. Eventually information is retrieved from memory automatically and without effort during the autonomous stage (see Logan, 1988; Rickard, 1997, for similar models). Within each stage, the strategies used become more efficient with practice; however, these improvements are relatively small (Ackerman & Woltz, 1994; Strayer & Kramer, 1990). By comparison, switching from algorithmic processes to retrieval typically produces a much larger increase in efficiency (Ackerman & Woltz, 1994; Strayer & Kramer, 1990). That is, within-strategy improvements are fairly limited, whereas this type of strategy shift produces large improvements in performance.

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The shift from slow and effortful algorithmic processes to fast and relatively effortless retrieval processes has been demonstrated in a number of verbal and mathematical domains including: sight word reading (Siegler, 1988a), reading comprehension (Rawson & Middleton, 2009), simple arithmetic (Delaney et al., 1998; Reder & Ritter, 1992; Siegler, 1988a, 1988b; Tenison & Anderson, 2016), complex novel arithmetic (Rickard, 1997; Wilkins & Rawson, 2010), alphabet arithmetic (Haider & Frensch, 2002; Wilkins & Rawson, 2011, 2013), and paired associate learning (Ackerman & Cianciolo, 2000; Ackerman & Woltz, 1994; Wilkins & Rawson, 2010). However, each of these tasks involves verbal or numerical stimuli. To our knowledge, no studies have tested whether a similar shift from algorithm to retrieval occurs for dynamic spatial tasks, such as hitting or catching a ball.

Interception in Ball Sports

Ball sports are a particularly interesting domain for skill acquisition research, because there is both a motor component—moving into position to intercept a ball—as well as a cognitive component—knowing when and where to move to intercept the ball. Regarding the motor component, the time needed to move to a target area is a function of the distance and the size of the target (i.e., Fitts' Law; Fitts, 1954). The mechanisms behind the progression from effortful to automatic performance of complex motor patterns result from neuronal changes to the motor cortex (Doyon et al., 2002; Hikosaka, Nakamura, Sakai, & Nakahara, 2002; Puttemans et al., 2005). Regarding the cognitive component, many studies have examined the visual properties used to estimate a ball's arrival time—the time to collision (Bootsma & Oudejans, 1993; Gray, 2002; Gray & Regan, 1998, 2006; Regan, 1997). Specifically, changes in the image of the object on the retina (e.g., rate of expansion, change in position, change in texture) can be used to accurately estimate time to collision (Gray, 2002; Gray & Regan, 1998; Lee, 1976). Additionally, binocular cues (Gray & Regan, 1998) and prior knowledge of the ball's size (Bootsma & Peper, 1992) can be used to aid time to collision estimates.

Similar to time to collision, a number of studies have identified visual cues used to algorithmically guide both body positioning (running to the point of collision; Mcbeath, Shaffer, & Kaiser, 1995; Michaels & Oudejans, 1992; Shaffer, Marken, Dolgov, & Maynor, 2015) and interceptive movements of the limbs (place the hand in position to catch or knowing where to swing a bat or racket to hit the ball; Ledouit, Casanova, Zaal, & Bootsma, 2013; Peper, Bootsma, Mestre, & Bakker, 1994). However, there is controversy regarding how people use these visual cues to perform interceptive tasks. Some research supports an *online approach* (also known as prospective control), in which people use continuous visual feedback to guide their movements (Casanova, Borg, & Bootsma, 2015; McLeod & Dienes, 1996; Shaffer et al., 2015; Zhao & Warren, 2015). For example, baseball players fielding fly balls, often approach the ball gradually, adjusting their pace and arriving just in time to catch the ball (Mcbeath et al., 1995); see (Shaffer et al., 2015 for a similar example from American Football). Essentially, the person does not know where the ball will land, only how to adjust and arrive as it does. For other tasks people appear to use a *model-based approach* (also known as projective control), where internal models of the environment predict the future location of the ball (de la Malla & Lopez-Moliner, 2015; Diaz, Cooper, Rothkopf, & Hayhoe, 2013; Zago, McIntyre, Senot, & Lacquaniti, 2009).[1] For example, cricket and squash players do not track the ball continuously during its flight. Rather they track the ball for a short duration, then shift their eyes to the bounce point, and track the ball from there (Diaz et al., 2013; Hayhoe, Mennie, Gorgos, Semrau, & Sullivan, 2004; Land & McLeod, 2000). As additional evidence for the model-based approach, people can catch falling objects and intercept balls even when vision is occluded during all or part of the trajectory (de la Malla & Lopez-Moliner, 2015; Zago et al., 2004; Zago & Lacquaniti, 2005; but see Bennett, Barnes, Simon, & Barnes, 2003). Model-based approaches may be particularly important when the time for responding is relatively limited and responses (e.g., swinging a bat) need to be initiated well in advance of the balls arrival.

Integrating Cognitive Skill Acquisition and Interception

Studies of interception have focused on how people algorithmically determine when and where interception will occur, but rarely consider how this process might change over time. It is possible that substantial practice allows for a retrieval-based strategy when the same trajectory is encountered multiple times. This may particularly be the case in sports where a limited number of trajectories will keep the ball in play. There are several important differences between spatial interception tasks and the verbal and mathematic tasks used in previous studies of retrieval shift. First, the algorithms used in verbal and mathematical domains (e.g., sounding out words, complex mathematical computations) are initially learned only with great effort and remain effortful to execute. By contrast, even infants appear to have some innate understanding of physics and motion (Baillargeon, 1987) and the spatial extrapolation assumed to occur in the model-based approach, may be relatively effortless and automatic (Freyd, 1987). If spatial algorithms are relatively efficient, then a direct retrieval strategy may not offer an advantage and thus may not be adopted.

Spontaneous shifts from algorithmic to retrieval strategies have been shown in verbal and mathematical domains. Our goal was to test whether a shift from algorithmic to retrieval strategies could spontaneously occur in a dynamic spatial task. There are several ways to identify when a participant has adopted a retrieval-based strategy. The most common method is to model response times (e.g., Tenison & Anderson, 2016). Another option, given that retrieval shifts are item specific (Touron, 2006; Wilkins & Rawson, 2011) is to test for differences in performance between repeated and novel items (Wilkins & Rawson, 2011). If repeated items are performed as well as novel items, it suggests that task improvements resulted from item-general improvements to the algorithm. However, if performance is better for repeated compared to novel items, then the item-specific improvements could be the result of an item-specific shift from algorithm to retrieval.

[1] Note that there is considerable disagreement among researchers as to whether either online or model-based approaches alone can account for the entirety of human performance (see Diaz, Phillips, & Fajen, 2009; Zago, McIntyre, Senot, & Lacquaniti, 2009; Zhao & Warren, 2015 for reviews). The nature of the underlying algorithms is beyond the scope of the current experiments.

Additionally, participants are often asked to report whether they used an algorithm or retrieval strategy after each trial. Immediate strategy self-reports have been validated by response time and eye-tracking data in previous studies using verbal and numerical materials (Delaney et al., 1998; Frank, Touron, & Hertzog, 2013a; Rickard, 1997; Touron, Hertzog, & Frank, 2011). However, there are a number of differences between our paradigm examining fast-paced dynamic spatial skill acquisition and paradigms examining static verbal or numerical tasks. Of particular concern is that metacognitive awareness of strategy use in a dynamic spatial task may be poor. For example, despite the assumption that experts perform tasks automatically while novices recruit cognitive control, expert and novice athletes self-report similar levels of automaticity (Thomas, Murphy, & Hardy, 1999). A second concern is that immediate strategy reports could be potentially reactive in our paradigm. Thus, we used retrospective strategy reports at the end of the task.[2]

Similar to verbal and mathematical tasks, we minimized the role of motoric processes and learning motoric patterns; moving a mouse along a single vertical plane was the only motoric process required. Thus, our task was designed to capture cognitive skill acquisition, rather than motor skill acquisition. In two experiments we used repeated trajectories in a task similar to the video game Pong. Specifically, we decreased the time participants had for responding thereby increasing the distance over which they had to mentally extrapolate the position of the ball. We later introduced novel trajectories without warning.

We hypothesized that if participants meet the increased time constraints by merely increasing the speed at which they perform the algorithm, then they should maintain a high degree of accuracy even on novel trajectories. However, if participants switch to a direct retrieval strategy to meet the increased time constraints, then they should perform better on repeated relative to the novel trajectories. How much better is an open question. Although retrieval strategies produce large benefits in studies using verbal and mathematical materials, the magnitude of the benefit depends on the efficiency of the algorithm (Touron & Hertzog, 2004). If spatial algorithms are relatively efficient, then performance differences may be relatively small even at the difficult deadline. Note that unlike previous studies (Gray, 2002; Savelsbergh, Williams, Van der Kamp, & Ward, 2002; Shim, Carlton, Chow, & Chae, 2005; Shim, Miller, & Lutz, 2005; but see Delle Monache, Lacquaniti, & Bosco, 2015), the game Pong takes place on a plane perpendicular to the performer's line of sight. This is critical because it eliminates the potential confound that occurs if a participant has prior experience with ball sports (and has perhaps encountered identical trajectories in the past).

Experiment 1

Method

Participants. Seventy-seven students enrolled in General Psychology I at Case Western Reserve University participated in exchange for partial course credit.

Tasks and materials.

Pong task. This task was created via E-prime 2 (Schneider, Eschman, & Zuccolotto, 2002) and performed on 23-in. Optiplex 9030 computer screens. Stimuli were presented at a resolution of 1920 × 1080 pixels at a refresh rate of 59 Hz. In each trial, participants viewed a ball launched from the left side of the screen (see Figure 1). The ball traveled from the launch point to the right side of the screen bouncing once on the bottom of the screen. The ball moved with a constant horizontal velocity of 565 pixels per s. The launch angle was manipulated by changing the vertical velocity of the ball. The vertical velocity of the ball was then subjected to a gravity that negatively accelerated the ball at 11 pixels per s squared. The elasticity of the ball was set to 95% (after hitting the bottom of the screen, the ball reversed vertical direction by multiplying the vertical velocity by -0.95). Thus the ball followed the laws of the physics and moved in realistic ways across the screen, other than ignoring any effects from friction, spin, wind, or air resistance (that is, the ball moved as if in a vacuum). Each trajectory lasted 3.4 s.

Participants used the mouse to position a paddle—located 80 pixels from the right side of the screen—so that it would intercept the ball. Importantly, participants had to click the left mouse button to "freeze" the paddle into position before the ball crossed a vertical line—a response deadline—on the screen. After the left mouse button was clicked, the paddle would turn black and would no longer move with the mouse until the next trial. If the ball hit the paddle it bounced back to the left, again following the laws of physics. If the ball missed the paddle, the ball would exit off the right side of the screen. Similarly, if participants did not click the paddle into place prior to the ball crossing the deadline, the paddle would disappear and the ball would exit off the right side of the screen. Regardless of whether the ball hit the paddle, a delay of 1.4 seconds provided participants with ample time to process the visual feedback of the ball hitting the paddle and bouncing back toward the left side of the screen, or missing the paddle and exiting off the right side of the screen.

Before each trial, the participant clicked a start button on the right side of the screen halfway between the top and bottom of the screen. This ensured that the paddle was in the same location at the start of each trial. Thus participants could learn not only where the paddle must be positioned for a given trajectory, but also how far up or down the mouse must be moved for that trajectory before clicking. Note that this allows for a potential direct stimulus to motor-response learning. However, the motor sequence itself (moving the mouse) was relatively simple and well-practiced in all participants. Thus, no new complex motor skills had to be developed during the course of the experiment. This is a distinct advantage over more naturalistic tasks like training novices to hit or catch baseballs, or using experienced players who made have encountered the same trajectories in the past.

Two different difficulty levels were used during the task. First participants performed the task at an easy difficulty level to become familiar with the task and the trajectories. During this learning phase, participants clicked the paddle into position before the ball reached a vertical red line, positioned 140 pixels from the right side of the screen. Later in the task, participants advanced to the difficult phase where they clicked the paddle into position before the ball reached a vertical gray line, positioned 650 pixels from the

[2] A previous study on retrieval-based strategy use found that retrospective strategy reports correlated highly with immediate strategy reports ($r = .85$, $p < .001$; Frank, Touron, & Hertzog, 2013b).

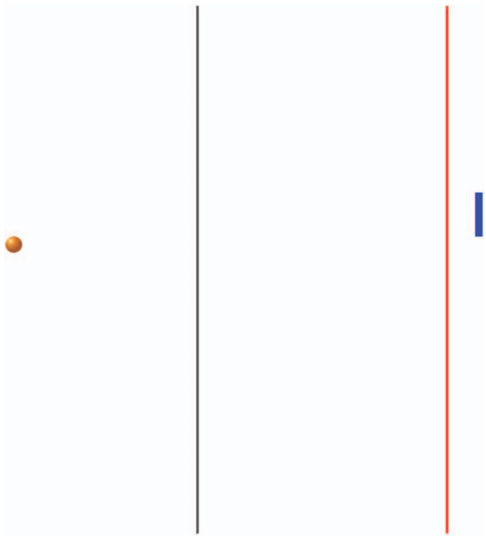

Figure 1. Screenshot of the Pong task showing the ball in mid-trajectory, paddle (black [blue in the color version] rectangle right side of screen), learning phase deadline (dark gray [red in the color version] line near the paddle), and earlier difficult phase and critical phase deadline (dark gray line closer to the ball). See the online article for the color version of this figure.

right side of the screen (see Figure 1). The paddle remained in the same position on the right side of the screen for both deadlines and the goal was to intercept the ball with the paddle on the right side of the screen in both cases. The only difference between the two deadlines was how early in the ball's trajectory the participant was required to position and commit to the paddle position. Participants were initially told to click the paddle into place before the ball reached the red line but were warned that,

> [l]ater in the task, the paddle will remain next to the red line, but we will increase the difficulty by requiring you to click the paddle into position before the ball reaches the GRAY line. Therefore, you should try to click the paddle into position as early as possible during the easier part of the experiment so that you are ready when the experiment gets harder.

These difficulty levels were selected on the basis of extensive piloting. The decision to place the initial deadline 140 pixels from the right of the screen was based on pilot data ($n = 7$) with various difficulty levels (difficulty was adjusted based on participant performance). We found that learning was considerably faster when participants started with this easier deadline before advancing to more difficult levels. The more difficult deadline was based on maximum performance levels reached during piloting.

Learning phase. Participants completed 20 blocks of trials during the Learning Phase (clicking before the ball reached the red line close to the paddle).[3] Each block contained the same four repeated trajectories (see Figure 2A). Presentation order for the four trajectories was randomized within each block.

Difficult phase. Participants next completed 20 blocks of trials during the more difficult phase (clicking before the ball reached the gray line further from the paddle). Each block contained the same four repeated trajectories used in the learning phase (see Figure 2A). Before the difficult phase began, participants saw a screen that said, "You will now have to position the paddle and click it into place before the ball reaches the GRAY line."

Critical phase. For the critical phase, participants completed 14 blocks of trials at the same difficult phase deadline. Each block contained five trials: the four repeated trajectories plus either one "near-extrapolation" or one "far-extrapolation" trajectory. Near-extrapolation trajectories had launch points within the same range as the repeated trajectories (see Figure 2B). By contrast, far-extrapolation trajectories had launch points that originated either above or below the practiced range of the repeated trajectories (see Figure 2C). Each near- and far-extrapolation trajectory was used only once during the critical phase. Participants were not told that any trajectories were repeated or that new trajectories would be added.

Other measures. Participants completed a measure of perceptual speed (Pattern comparison test; Salthouse, 1993); a measure of psychomotor speed (Connections Test Part A; [Salthouse et al., 2000]); a computerized survey of video game experience (see the online supplemental materials); a measure of spatial reasoning (Paper folding Test VZ-2-BRACE; Ekstrom, French, & Harman, 1976); and a posttask questionnaire. The posttask questionnaire (see the online supplemental materials) asked participants about their observations of the task, and to indicate how much they agreed with eight statements about the task (e.g., "I found the task with the ball and paddle interesting") using the following options: 1 = *very false for me*, 2 = *somewhat false for me*, 3 = *somewhat true for me*, or 4 = *very true for me*. Most importantly, participants were also asked:

> You could decide where to place the paddle by mentally tracing the path of the ball or by using your memory for where a given trajectory would land on the basis of previous times you saw that trajectory. Which method did you primarily use near the END of the task?

Participants could choose from among "tracing," "memory," "both," and "unsure/other."

Procedure. Participants first completed the two paper-and-pencil measures: the measure of perceptual speed and the measure of psychomotor speed. Next they completed the computerized survey of video game experience followed by the computerized test of spatial reasoning. Participants then completed the Pong task followed by the posttask questionnaire. The entire procedure lasted approximately 1 hr.

Results

Alpha level was set to .05. Reported p values for repeated-measures analyses of variance (ANOVAs) are Greenhouse-Geisser corrected p values. Using uncorrected or Huynd-Feldt corrected p values produced the same pattern of results. Our primary dependent variable is Pong task accuracy—the percentage of trials in which the participant successfully hit the ball (see Figure 3).

[3] Pervious research using word-pairs and mathematical stimuli indicates that younger adults typically adopt high rates of retrieval use (>80%) for a set of 12 items after roughly 10–20 repetitions (Rickard, 1997; Touron & Hertzog, 2009; Touron, Swaim, & Hertzog, 2007). Given our potentially less distinct and confusable stimuli, we opted for 20 repetitions of only four stimuli.

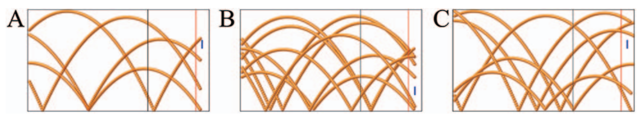

Figure 2. Experiment 1 trajectories. Panel A shows the four repeated trajectories used across all phases of the task. Panel B and C show the "near-extrapolation" (B) and "far-extrapolation" (C) novel trajectories used in addition to the repeated trajectories during the critical phase. See the online article for the color version of this figure.

Results for response times and distance from the ball on missed trials can be found in the supplemental materials.

Repeated trajectory accuracy. To test whether accuracy for repeated trajectories decreased as a result of difficulty level or adding in new trajectories, we compared accuracy for repeated trajectories in the last five blocks of the learning phase, the last five blocks of the difficult phase, and the full 14 blocks of the critical phase using a repeated-measures ANOVA. We used the last five blocks of the first two phases to test performance at that difficulty level after acclimation. The main effect of phase was significant, $F(2, 152) = 22.77$, $p < .001$. Accuracy was higher on the easier learning phase compared with the difficult phase, $t(76) = 2.71$, $p = .008$, $d = 0.31$. Thus, even after a similar level of practice at each difficulty level, participants were less accurate at the later deadline compared to the easier learning phase deadline. Accuracy on repeated trajectories was also higher on the difficult phase compared with the critical phase, $t(76) = 4.14$, $p < .001$, $d = 0.47$. Thus, the addition of new trajectories appears to have disrupted performance on the repeated trajectories. If participants are using a retrieval strategy during the difficult phase they may begin to hesitate on repeated trajectories or switch back to an algorithmic strategy for all trajectories—hence the decline in performance for repeated trajectories. See Figure 4.

Critical phase accuracy. For the critical phase, a repeated-measures ANOVA of trial type (repeated, near-extrapolation, far-extrapolation) revealed a significant main effect, $F(2, 152) = 50.79$, $p < .001$. Accuracy was greater for repeated trajectories

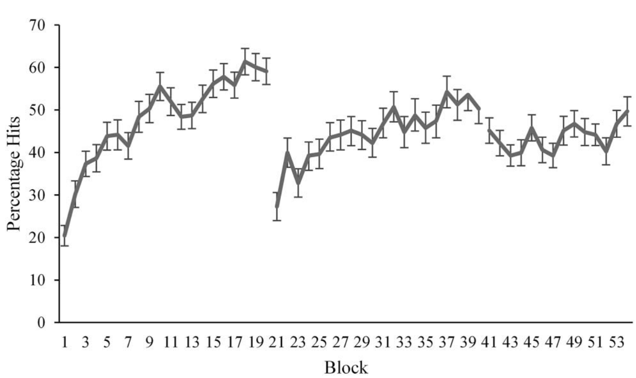

Figure 3. Experiment 1 percentage hits over blocks. Blocks 1 through 20 represent the learning phase; Blocks 21 through 40 represent the difficult phase; Blocks 41 through 60 represent the critical phase. Error bars represent + 1/–1 standard error of the mean. Participants were instructed to attempt to respond early during the learning phase to prepare for the difficult phase.

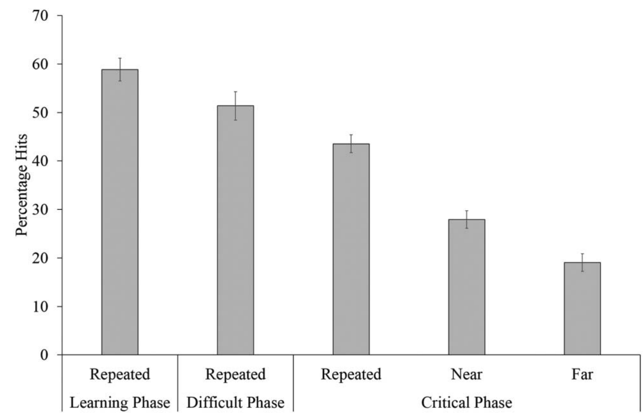

Figure 4. Experiment 1 accuracy results (percentage intercepted) on the last five blocks of the Learning and Difficult Phases and the full 14 blocks of the Critical Phase. Error bars represent ±1 standard errors of the mean.

relative to both near-extrapolation, $t(76) = 6.65$, $p < .001$, $d = 0.76$, and far-extrapolation trajectories, $t(76) = 9.59$, $p < .001$, $d = 1.09$. Additionally, accuracy for near-extrapolation trajectories was greater than for far-extrapolation trajectories, $t(76) = 3.58$, $p < .001$, $d = 0.41$. See Figure 4.

Strategy reports results. The majority of participants ($n = 34$) indicated using a combination of algorithmic and retrieval strategies, followed by primarily using retrieval ($n = 23$) then algorithm ($n = 12$).

Repeated trajectory accuracy by strategy report. We examined accuracy for repeated trajectories to evaluate whether the observed decreases in accuracy—as a result of difficulty level or adding in new trajectories—were restricted to the retrieval or algorithm strategies. We focused on performance over the last five blocks of the learning phase and difficult phase and the repeated trajectories of the full 14 blocks of the critical phase. These were analyzed via a 3 (phase: learning, difficult, critical) × 3 (strategy report: algorithm, retrieval, both) within–between ANOVA (see Figure 5).

A main effect of phase, $F(2, 132) = 19.28$, $p < .001$, resulted from critical phase repeated trajectories being hit less often than either the learning phase, $t(34) = 5.71$, $p < .001$, $d = 0.98$, or the difficult phase, $t(34) = 5.32$, $p < .001$, $d = 0.91$ trials. Learning and Difficult Phase accuracy did not differ, $t(34) = 1.16$, $p = .254$. The main effect of strategy was not significant, $F(1, 66) = 1.12$, $p = .333$. However, a Phase × Strategy interaction emerged, $F(4, 132) = 3.16$, $p = .025$, such that phase was significant for the algorithm users, $F(2, 22) = 16.23$, $p < .001$, and the both-strategies group, $F(2, 66) = 11.72$, $p < .001$, but not for the retrieval users, $F(2, 44) = 2.25$, $p = .129$.

Critical phase accuracy by strategy report. If a direct retrieval strategy was responsible for the greater accuracy on critical phase repeated trajectories relative to new trajectories, then this effect should be restricted to the self-reported retrieval group. We tested this via a 3 (trial type: repeated, near-extrapolation, far-extrapolation) × 3 (strategy report: algorithm, retrieval, both) within–between ANOVA.

The main effect of trial type was significant, $F(2, 132) = 30.13$, $p < .001$. The main effect of strategy was not significant, $F(2,$

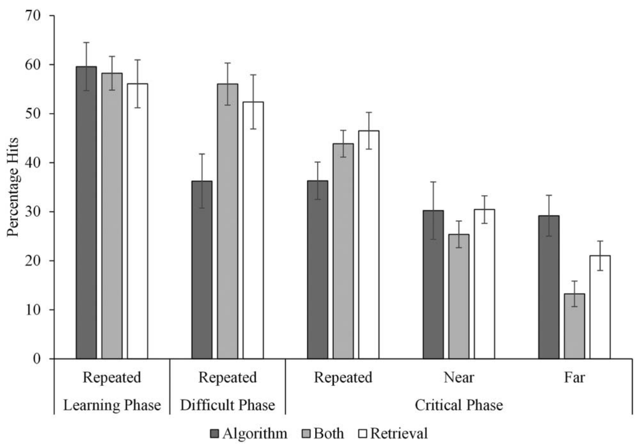

Figure 5. Experiment 1 accuracy results by self-reported strategy (percentage intercepted) on the last five blocks of the Learning and Difficult Phases and the full 14 blocks of the Critical Phase. Error bars represent ±1 standard errors of the mean.

66) = 2.10, p = .131. However, there was a significant Strategy × Trial type interaction, $F(4, 132) = 2.81$, $p = .028$.

We conducted separate follow-up ANOVAs for each strategy group. For the algorithm users, the main effect of trial type was not significant, $F(2, 22) = 0.71$, $p = .501$.

For retrievers, the main effect of trial type was significant, $F(2, 44) = 16.57$, $p < .001$. Retrievers' accuracy for repeated trajectories was significantly higher than both near-extrapolation, $t(22) = 3.44$, $p = .002$, $d = 0.72$, and far-extrapolation trajectories, $t(22) = 5.68$, $p < .001$, $d = 1.19$. Accuracy was also somewhat higher for near- compared to far-extrapolation trials, $t(22) = 2.20$, $p = .038$, $d = 0.46$.

For participants indicating they used both algorithmic and retrieval strategies, the main effect of trial type was significant, $F(2, 66) = 40.56$, $p < .00$. Accuracy for repeated trajectories was significantly higher than both near-extrapolation, $t(33) = 6.48$, $p < .001$, $d = 1.11$, and far-extrapolation trajectories, $t(33) = 8.41$, $p < .001$, $d = 1.44$. Accuracy was also somewhat higher for near-compared to far-extrapolation trials, $t(33) = 3.37$, $p = .003$, $d = 0.56$. See Figure S9.

Discussion

Participants intercepted repeated trajectories substantially more often compared to new trajectories (ds = 0.76 and 1.09), providing strong evidence for item-specific learning. The results are consistent with a shift from algorithmic to retrieval-based processing. They do not suggest a continued improvement in the use of a general spatial algorithm. Additionally, only participants self-reporting a retrieval-based strategy showed a benefit for repeated over novel trajectories.

Near-extrapolation trials were hit more often than far-extrapolation trials ($d = 0.41$). This could indicate that participants developed item-specific strategies that could be transferred to near- but not far-extrapolation trials. Alternatively, the far trials are more likely to land near either the top or bottom of the screen. Thus, the participant has to move the mouse farther from the initial start button on these trials, producing more errors.

Although Experiment 1 suggests that participants shifted to a retrieval-based strategy, it does not eliminate the possibility that equivalent performance might be achieved if participants instead continue to practice the algorithm on each trial. To test this hypothesis, Experiment 2 included an all-novel trajectory control group where participants could not shift to a retrieval-based strategy.

Experiment 2

Method

Participants. Sixty-three students enrolled in General Psychology I at Case Western Reserve University participated in exchange for partial course credit.

Tasks and materials.

Pong task. Experiment 2 used two versions of the Pong task. An "all-novel" control group saw 260 unique trajectories (no repetitions). A "repeated group" saw only four unique trajectories repeated until reaching a critical phase that introduced novel trajectories (similar to Experiment 1).

To obtain the number of unique trajectories needed for the all-novel group we used the full range of possible launch points along the left vertical axis of the screen. To make the repeated group comparable, a new set of four trajectories were selected for repetition. This new set of trajectories included launch points from the extreme upper and lower portions of the screen (see Figure 4). We also solicited open strategy reports earlier in the task (before the start of the critical phase) and expanded the number of critical phase trials, and thus, the number of novel trials in the repeated group.

Learning phase. All participants completed 20 blocks of trials at the easier deadline (clicking before the ball reached the red line close to the paddle). For the repeated group, each block contained the same four repeated trajectories (see Figure 6). Presentation order for the four trajectories was randomized for each block as in Experiment 1. For the all-novel group, trajectory selection was random.

Difficult phase. Before the difficult level training phase began, participants saw a screen that read, "STAGE 2. You will now have to position the paddle and click it into place before the ball reaches the GRAY line." Participants next completed 17 blocks of

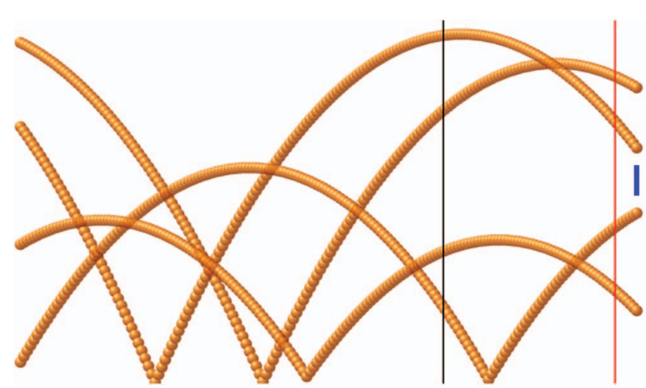

Figure 6. Experiment 2 repeated trajectories. See the online article for the color version of this figure.

trials at this difficulty level (clicking the paddle into place before the ball reached the gray line). For the repeated group, each block contained the same four repeated trajectories used in the Learning Phase. For both the repeated and all-novel groups, the 18th block of Phase 2 trials presented the four trajectories used for the repeated group (See Figure 6.). This allows us to compare performance across groups on the same trajectories just prior to obtaining the open strategy reports. We refer to this as the "comparison block." The open strategy report immediately followed and asked, "Please describe the strategies you used to perform the task during STAGE 2." Following the open strategy report, participants saw a screen that read, "STAGE 3. As in Stage 2 you will have to position the paddle and click it into place before the ball reaches the GRAY line." This screen was followed by two blocks of four trials with the same repeated trajectories for the repeated group and novel trajectories for the all-novel groups respectively. These two blocks were included to present the illusion that the task would not change following the open strategy reports.

Critical phase. In the critical phase, participants completed 20 blocks at the same difficult phase deadline. For the repeated group, each block contained five trials: the four repeated trajectories and one novel trajectory. Note that because the repeated trajectories include launch points at the extreme top and bottom of the screen, there is no near- versus far-extrapolation distinction in Experiment 2. Participants were not told that any trajectories were repeated or that new trajectories would be added. The all-novel group participants completed 20 blocks with five novel trajectories in each block.

Other measures. Participants completed a posttask questionnaire similar to the one used in Experiment 1. In Experiment 2, the strategy question was reworded to read as follows:

> You could decide where to place the paddle by mentally tracing the path of the ball, or by using your memory for where a given trajectory would land based on previous times you saw that trajectory. Which method did you primarily use near the END of STAGE 2?

Procedure. Participants first completed the Pong task followed by the posttask questionnaire. The entire procedure lasted approximately 45 min.

Results

Alpha level was set to .05. Reported *p* values for repeated measures ANOVAs are Greenhouse-Geisser corrected *p* values. Using uncorrected or Huynd-Feldt corrected *p* values produced the same pattern of results. As in Experiment 1, we focus our analyses on Pong task accuracy, see Figure 7. Results for response times and distance from the ball on missed trials can be found in the online supplemental materials.

Accuracy by condition. We first compared accuracy for repeated trajectories in the last five blocks of the learning phase, the last five blocks of the difficult phase (including the comparison block and the two blocks following the open strategy report), and the full 20 blocks of the critical phase using a 2 (group: repeated, all-novel) × 3 (phase: learning, difficult, critical) within–between ANOVA, with group as a between-subjects factor. Experiment 2 accuracy data can be found in Figure 8.

The main effect of group was significant, $F(1, 61) = 35.62$, $p < .001$, $d = 1.50$. Accuracy was higher for participants in the

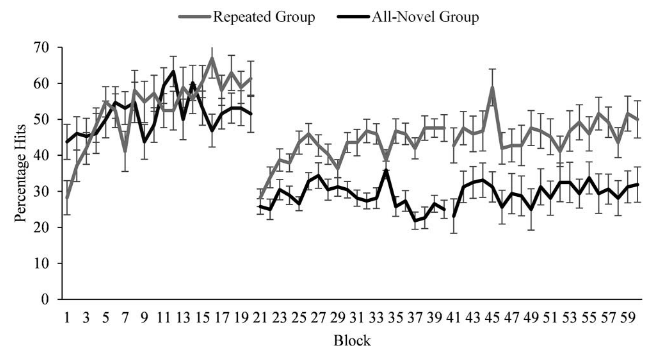

Figure 7. Experiment 2 percentage hits. Blocks 1 through 20 represent the learning phase; Blocks 21 through 40 represent the difficult phase; Block 38 represents the comparison block; Blocks 41 through 60 represent the critical phase. Error bars represent + 1/–1 standard error of the mean.

repeated group than the all-novel group. The main effect of phase was also significant, $F(2, 122) = 65.76$, $p < .001$. Accuracy was higher in the easier learning phase than in either the difficult phase, $t(62) = 7.93$, $p < .001$, $d = 1.00$, or critical phase, $t(62) = 9.61$, $p < .001$, $d = 1.21$. Difficult phase accuracy was not significantly different from accuracy on the critical phase, $t(62) = 0.54$, $p = .591$. However, these main effects were qualified by a significant Group × Phase interaction, $F(2, 122) = 4.02$, $p = .035$. To follow up on this interaction, we next conducted a pair of 2 (group) × 2 (phase) ANOVAs.

The first ANOVA examined the effects of group (repeated vs. all-novel) and phase (learning vs. difficult) on Pong task accuracy. The repeated group had higher average accuracy than the all-novel group, $F(1, 61) = 33.94$, $p < .001$, $d = 1.48$. Accuracy was higher in the learning phase than in the difficult phase, $F(1, 61) = 65.97$, $p < .001$, $d = 1.00$. A significant Group × Phase interaction resulted from a greater decrease in accuracy from the learning phase to the difficult phase for the all-novel group.

The second ANOVA examined the effects of group (repeated vs. all-novel) and phase (difficult vs. critical) on Pong task accuracy. Again, the repeated group had higher average accuracy than the all-novel group, $F(1, 61) = 33.94$, $p < .001$, $d = 1.09$. The difficult phase and the critical phase were not significantly different, $F < 1$. However, the ANOVA revealed a significant Group × Phase interaction, $F(1, 61) = 11.66$, $p = .001$. This interaction was driven by the all-novel group having significantly higher accuracy in the critical phase relative to the difficult phase, $t(31) = 3.55$, $p = .001$, $d = 0.37$, whereas the repeated group had similar accuracy in the critical phase and difficult phase, $t(31) = -1.72$, $p = .096$.

Importantly, performance was better in the repeated group across all three phases relative to the all-novel group (*p*s < .05). Hence, additional practice using the spatial algorithm did not lead to performance gains comparable to shift to retrieval. See Figure 7.

Repeated group critical phase accuracy. Similar to Experiment 1, we tested whether accuracy differed by trial type in the critical phase for the repeated group. Accuracy was higher for repeated trajectories compared with novel trajectories, $t(30) = 7.54$, $p < .001$, $d = 1.35$.

Comparison block accuracy. To ensure that the superior performance of the repeated group was not the result of the

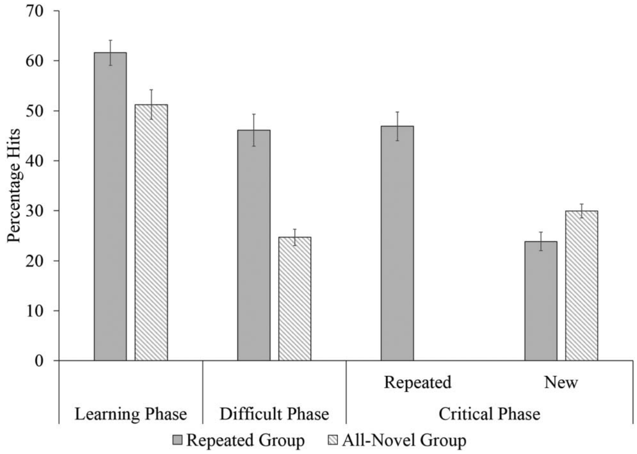

Figure 8. Experiment 2 accuracy results (percentage intercepted) on the last five blocks of the Learning and Difficult Phases and the full 17 blocks of the Critical Phase. Error bars represent ±1 standard errors of the mean.

repeated trajectories being easier (on average) compared with the novel trajectories, we examined performance between the repeated group and the all-novel group during the comparison block—where both groups saw the exact same four trajectories. For the all-novel group, this was the first time they saw these four trajectories, whereas the repeated group saw them for the 38th time. As in prior analyses, the repeated group ($M = 47.58$, $SE = 4.54$) was more accurate than the all-novel group ($M = 22.66$, $SE = 4.25$), $t(61) = 4.01$, $p < .001$, $d = 1.01$. Thus, the superior performance of the repeated group was not due to the trajectories selected for the repeated condition being inherently easier than the other trajectories.

Critical phase novel trajectory accuracy. Last, we compare critical phase accuracy for the repeated and all-novel groups on novel trajectories. Accuracy was significantly higher for the all-novel group than the repeated group, $t(61) = 2.63$, $p = .011$, $d = 0.66$.

Strategy reports results. In the repeated group, participants were nearly evenly distributed across algorithmic ($n = 10$), retrieval ($n = 11$), and both ($n = 9$) strategies. The majority of participants in the all-novel group indicated using an algorithmic strategy ($n = 18$), but surprisingly, some participants indicated using retrieval ($n = 5$) or both ($n = 8$) strategies.

Repeated trajectory accuracy by strategy report. We first compared accuracy for repeated trajectories in the last five blocks of the practice phase, the last five blocks of the difficult phase, and the full 20 blocks of the critical phase using a 2 (group: repeated, all-novel) × 3 (phase: learning, difficult, critical) × 3 (self-reported strategy: algorithm, retrieval, both) within-between ANOVA, with group and self-reported strategy as a between-subjects factors. These analyses collapsed across all of the difficult phase including the comparison and poststrategy report blocks. Note that "other" strategies were not included in these analyses because few people selected this option.

The main effect of group was significant, $F(1, 55) = 20.18$, $p < .001$, $d = 1.50$. Accuracy was significantly higher for participants in the repeated group. The main effect of strategy was not significant, $F(2, 55) = 1.79$, $p = .177$. The Group × Strategy ($F < 1$), Group × Phase, $F(2, 110) = 1.55$, $p = .221$, and Phase × Strategy interactions ($F < 1$) were not significant. However, the three-way interaction was also significant, $F(4, 110) = 4.45$, $p = .005$. Self-reported retrieval users performed better across phases in the repeated group. By contrast, only learning phase accuracy differed by self-reported strategy use in the all-novel group.

Critical phase accuracy by strategy report.

Repeated group critical phase accuracy. A 3 (strategy: algorithm, retrieval, both) × 2 (trial type: repeated, novel) within–between ANOVA tested whether critical phase accuracy differed by trial type and self-reported strategy for the repeated group. The main effect of strategy was not significant, $F(2, 27) = 1.21$, $p = .315$. The main effect of trial type was significant, $F(1, 27) = 64.58$, $p < .001$. However, this was qualified by a significant Strategy × Trial Type interaction, $F(2, 27) = 4.07$, $p = .029$. Accuracy was higher for repeated trials regardless of whether participants reported using an algorithmic, $t(9) = 2.79$, $p = .021$, $d = 0.88$, a retrieval strategy, $t(9) = 2.79$, $p = .021$, $d = 2.32$, or a combination of both strategies, $t(8) = 3.85$, $p = .005$, $d = 1.28$. However, the difference in accuracy was greater when retrieval

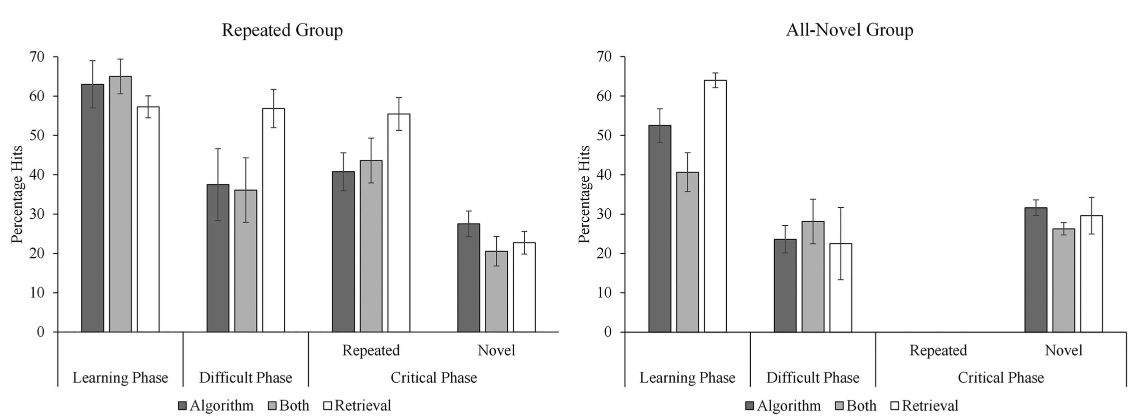

Figure 9. Experiment 2 accuracy results by self-reported strategy (percentage intercepted) on the last five blocks of the Learning and Difficult Phases and the full 17 blocks of the Critical Phase. Error bars represent ±1 standard errors of the mean.

was reported compared to when algorithm use was reported only, $t(19) = 3.07$, $p = .006$, $d = 1.34$ (all other comparison $ps > .19$).

All-novel group critical phase accuracy. A three-way (strategy: algorithm, retrieval, both) between-subjects ANOVA tested whether critical phase accuracy differed by self-reported strategy in the critical phase for repeated group. The main effect of strategy was not significant, $F(2, 28) = 1.26$, $p = .299$. See Figure 9.

Critical phase novel trial accuracy. Last, we ran a 2 (group: repeated, all-novel) $\times$ 3 (strategy: algorithm, retrieval, both) between-subjects ANOVA comparing accuracy on novel trials during the critical phase. The main effect of group was significant, $F(1, 60) = 4.79$, $p = .033$, $d = 0.66$, with higher accuracy in the all-novel group. The main effect of strategy, $F(2, 60) = 2.33$, $p = .107$, and the Group $\times$ Strategy interaction ($F < 1$) were not significant.

Discussion

As in Experiment 1, we found that performance was superior for repeated trajectories relative to novel trajectories. We observed this for trials within the repeated group ($d = 1.35$) as well as when comparing the repeated group to the all-novel group ($d = 1.01$). This finding is consistent with a shift from algorithm to direct retrieval strategies. These results mirror those in verbal and mathematical tasks (e.g., Rawson & Middleton, 2009; Rickard, 1997).

It is noteworthy that participants who did not have the opportunity to shift to retrieval—those in the all-novel group—performed better on novel trials than participants in the repeated group ($d = 0.66$). This effect does not appear to be driven by practice improving algorithmic performance. As can be seen in Figure 7, participants in the all-novel group did not improve with practice once they needed to respond at the difficult deadline. Instead, the explanation for this difference appears to be driven by lower performance by participants in the repeated group. These participants may have developed a habit of using retrieval and struggled to switch back to the algorithm when a trajectory was not recognized (a switch cost; e.g., Vandierendonck, Liefooghe, & Verbruggen, 2010). It is possible that participants in the repeated group occasionally mistook novel trajectories for practiced trajectories and attempted to use retrieval on these trials. Previous studies using novel math problems have found that people will erroneously choose to retrieve novel items that resemble practiced items (Reder & Ritter, 1992). Either or both of these explanations might be responsible for why participants in the repeated group performed more poorly on novel trials than those in the all-novel group.

Surprisingly, many participants in the all-novel condition indicated using a retrieval-based strategy. However, their performance was similar to other participants in their condition. It is possible that participants attempted to use retrieval on trajectories that were similar but not identical. Indeed, participants may have attempted retrieval to get a rough estimate of the ball's future location, then attempted to adjust algorithmically from there. Although such a strategy could be beneficial during the learning phase, this strategy would not be effective later in the task as the difficult phase does not allow for last second adjustment. Alternatively, people may simply have poor metacogntive awareness of how they process and respond to dynamic visual spatial information.

General Discussion

Studies of interception have focused on how people algorithmically determine when and where the interception will occur but rarely consider how this process might change over time. In two experiments we found superior performance for familiar trajectories relative to unfamiliar trajectories in a dynamic spatial skill acquisition task, consistent with a shift from algorithm to retrieval-based processing. The differences in performance between familiar and unfamiliar trajectories was large ($ds > 0.76$). This was particularly pronounced in Experiment 2 where participants who received repeated trajectories outperformed those who received all novel trajectories even at an easy difficulty level.

An alternative explanation is that participants performed better on repeated trials not because they used a retrieval-based strategy, but because of item-specific algorithm speed-up. That is, having executed the algorithm using the same values previously (the same angle and trajectory start points) may produce a priming effect, where the algorithm becomes more efficient for those specific trials. Future research looking at neurological correlates of spatial algorithms and direct retrieval strategies could potentially disambiguate these two possibilities. Specifically, changes in hippocampal activation should accompany a shift to retrieval-based strategies.

Performance was generally better at the later deadline (learning phase) rather than the early deadline (difficult phase) even for repeated trials. There are two potential explanations for this finding. Trajectories may be less distinct early on and more easily recognizable later in the trajectory. This would lead to occasional confusion regarding different trajectories at the early deadline resulting in errors. Alternatively, even if retrieval-based strategies are used early in the trajectory to position the paddle, visual feedback could be monitored as a "back-up" strategy up until a response needs to be made. This later explanation is somewhat consistent with Logan's (1988) instance theory of automaticity, in which the algorithm and retrieval search strategies are activated simultaneously: Whenever one process—algorithm or retrieval search—is completed, a response is made. Bajic and Rickard (2009, 2011) argued against instance theory, finding that simultaneous algorithm and retrieval execution is rare in numerical tasks. However, in dynamic spatial tasks, there may be a benefit to combining retrieval and algorithmic processes. Participants could use a retrieval strategy to get the paddle into position early (decreasing the likelihood of a miss due to a slow response) while also waiting until the last moment to respond—allowing for late-trajectory error corrections. Participants in the repeated condition in Experiment 2 performed better even at the early deadline relative to those in the all-novel condition, consistent with this explanation. However, future studies including continuous mouse tracking data could better address this possibility. A similar combination of strategies may occur in everyday tasks where memory-based strategies are coupled with algorithmic model-based approaches and online approaches to guide action.

Typical studies of retrieval shift use response times as indicators of performance improvements (e.g., Tenison & Anderson, 2016). Participants are instructed to perform the tasks as quickly as possible without sacrificing accuracy and are rewarded by finishing the experiment in less time. The downside to this approach is that some participants may prioritize speed and accuracy differently. Many laboratory retrieval-shift paradigms combat this by using tasks where accuracy greater than 80% is easily obtainable or required (e.g., Ackerman & Woltz, 1994; Rickard, 1997; Tenison & Anderson, 2016). The participants in our experiments had to wait for the ball to reach the paddle before the next trial could begin. Therefore, there is no inherent reward for quick responding. Thus, we avoided potential speed–accuracy trade-offs by using a response deadline instead of merely attempting to encourage early responding. The downside to this approach is that it does not allow for complex response time modeling that could dissociate between Fitts and Posner's (1967) associative and autonomous stages (as in Rickard, 1997 and Tenison & Anderson, 2016).

It could be argued that years of experience with physics in the natural world may result in a memorization of most common trajectories (particularly those that occur over a short distance over a small time frame). However, the strong item-specific learning observed in our Experiment argues against this possibility. Thus, learning in spatial tasks may be both item specific and task specific. Alternatively, it is possible that the general lack of improvement in the (Experiment 2) all-novel group was the result of spatial algorithmic ability being at ceiling because of a lifetime of experience. The algorithms may even be fully automatized and relatively effortless, even if suboptimal in the Pong task. Dual-task conditions have often been used to assess automaticity in processing. Future research in this area could examine whether performance on this task degrades under dual-task conditions, which would indicate that performance is effortful and cognitively demanding. By contrast, if performance remains at a high level while performing a secondary task, then performance is thought to be automatized and cognitively undemanding. Likewise, neuroimaging could be used to identify whether spatial tasks such as ours rely on brain regions associated with effort and cognitive control (i.e., the prefrontal cortex; Puttemans, Wenderoth, & Swinnen, 2005).

We did not intend to directly address the question of whether people use online or model-based approaches in dynamic spatial tasks. However, our paradigm necessitates a model-based approach at the difficult deadline—participants could not monitor the ball's motion until just before interception. Our findings are consistent with previous studies indicating that people can use a model-based approach to perform dynamic spatial tasks (Diaz et al., 2013; Hayhoe et al., 2004; Land & McLeod, 2000; Zago et al., 2004; Zago & Lacquaniti, 2005). Zhao and Warren (2015) suggest that people do not typically rely on model-based approaches when an online approach is viable. However, we found that repeated trajectories led to superior performance on both the learning phase, where online approaches are possible, and difficult phase, where only model-based approaches are possible. This suggests that, when possible, people may shift away from either online or model-based approaches, toward a retrieval-based strategy.

The current studies are consistent with the hypothesis that direct retrieval shifts play a role in real-world spatial skill acquisition where fast responses are needed. For example, tennis players may use direct retrieval strategies to anticipate the location of the tennis ball from a serve. The large effects found in this study also suggest that when viable, retrieval may produce a substantial advantage. However, the task used in the current studies differs from real-world spatial tasks in several ways.

First, our studies did not manipulate time to collision—an important variable for timing swings in sports like baseball, tennis, and hockey. Instead, our constant horizontal speed produced a single collision time with two response deadlines. From the time the participant clicked the mouse to start the trial until the time the ball arrived at the paddle was perfectly consistent across difficulty levels. Thus, participants in our experiments may have determined time to collision based on algorithmic properties (as in Bootsma & Oudejans, 1993), or they may have memorized the interval and responded using an internal model of time as opposed to continuous visual feedback. Regardless, this was consistent across all item types and conditions, and thus cannot account for the item-specific learning in our experiments. Our task was additionally simplified by removing variables such as wind, spin, or air resistance that have to be dealt with in many real-world tasks. We also used only four repeated trajectories to accelerate the stimulus-response learning in our task. Real-world tasks often involve a broader array of possible trajectories, but also more extensive learning periods.

Second, to prevent prior expertise with spatial tasks, such as ball sports, from influencing the results, the task occurred in only two dimensions and occurred on a perpendicular plane (as opposed to a first-person perspective). By using the mouse—something highly familiar and well-practiced for most college students, we also eliminated the need to develop motor coordination and speed necessary for most ball sports.

Last, our task environment was relatively impoverished; participants saw only the ball, paddle, and deadlines. In real-world tasks, other visual cues, such as the body language of the one's opponent may provide additional information that could be useful for anticipating the future ball location either algorithmically or using retrieval (Abernethy & Russell, 1987; Takeuchi & Inomata, 2009; Williams, Ford, Eccles, & Ward, 2011). Future research should experimentally manipulate each of these factors to better understand how they influence shifts to direct retrieval in fast-paced spatial tasks. It is possible that as the number of potential trajectories and external factors (such as wind) increase, the shift to direct retrieval may be substantially delayed.

Conclusion

We establish that item-specific learning produces a substantial benefit on spatial tasks similar to those previously observed for verbal and mathematical tasks. This finding is consistent with theories suggesting a shift from algorithmic to retrieval-based processing. These studies provide an important first step toward understanding the potential role of retrieval processes in spatial skill acquisition.

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