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Implicit motor learning and complex decision-making in time constrained environments.

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Abstract

The cost effective nature of the implicit (procedural) knowledge that supports expert motor behavior typically allows surprisingly efficient performance when time constraints necessitate that decisions and actions are executed in close proximity. The less cost effective nature of the explicit knowledge structures that support novice motor behavior leaves performance vulnerable to disruption however. We argue that if novices learn the motor component of performance implicitly rather than explicitly, attention can be directed more easily to decision-making leaving performance less vulnerable. Participants learned a table tennis shot implicitly by analogy learning or explicitly by specific verbal instructions. Motor performance and movement kinematics were assessed under conditions that required a concurrent low complexity or high complexity decision regarding where to direct each shot. Disruption of performance was evident for the high complexity but not the low complexity decision, and only in participants who learnt explicitly. It was concluded that implicit motor learning encourages motor control that is more cognitively efficient than explicit motor learning, so performance remains more stable in situations that require a complex decision to be made in tandem with a motor action.

Key words: analogy learning, explicit instructions, procedural knowledge, movement kinematics, cognitive load, expertise

Implicit motor learning and complex decision making in time constrained environments.

Appropriate decision-making requires the integration of perceptual information with knowledge obtained from prior experiences and places varying demands on cognitive resources, depending on the complexities of the task (e.g., Raab, 2003; Sève, Saury, Theureau, & Durand, 2002) and the extent to which performance is dependent on working memory (Jameson, Hinson, & Whitney, 2004).

The highly efficient way in which expert performers interface with their specialist environment is characterized by an ability to process multiple streams of the information that is needed for effective perception-action interaction. If the environment is time constrained, decision-making and movement execution must be performed in close temporal proximity. For example, to hit a forehand winner past an opponent while running demands appropriate movement selection (e.g., should the shot be hit down the line, across the court, deep, short, with under spin or topspin) coupled with immediate and effective movement execution.

One explanation of the highly efficient decision-making skills of experts is that, over time, there is a gradual change in the nature of the knowledge structures that support their motor performance, with an increasing degree of implicit (unconscious) control and a decreasing level of explicit (conscious) control. In contrast to conscious control processes, implicit processes are faster and are organized in more sophisticated structures that are represented as non-conscious procedural knowledge that can be accessed automatically (e.g., Anderson, 1983; Lewicki, Hill, & Czyewska, 1992; Masters & Maxwell, 2004; Shiffrin & Schneider, 1977; Willingham, 1998). Implicit processes are, therefore, independent from working memory, leaving the resources of the expert available to perform other tasks, such as decision-making (for a review of the theoretical architecture and function of working memory, see Baddeley, 2003). In contrast, explicit processes are dependent on working memory for the retrieval of consciously accessible (declarative) knowledge to control movement on-line (Maxwell, Masters, & Eves, 2003). Motor behavior that is highly explicit will be dependent on working memory, so the demands caused by multiple task requirements are likely to overload the performer and cause disruptions to performance.

In a test of this theory, Poolton, Masters, and Maxwell (2006) argued that disrupted motor performance is less likely to occur if the motor component of performance is learnt implicitly, rather than explicitly, because more resources will be available for decision-making. Implicit motor learning techniques are thought to advance implicit control and have been shown to engender resistance to disruption from additional cognitive loads (e.g., Maxwell, Masters, Kerr, & Weedon, 2001), moderate psychological pressure (Hardy, Mullen, & Jones, 1996; Masters, 1992), and, more recently, physiological exertion (Poolton, Masters, & Maxwell, in press).

Using a table tennis task, Poolton et al. (2006) trained participants explicitly (via step-by-step instructions) and implicitly (via an analogical instruction, see Liao & Masters, 2001) and tested performance in conditions that required a low complexity decision or a high complexity decision regarding the direction in which to hit the ball. Differences between the treatment conditions were only evident when high complexity decisions were required, with disruption of motor performance in the explicit condition but not the implicit (analogy) condition. In fact, performance in the implicit condition appeared to improve when participants were required to process high complexity decisions, suggesting greater processing efficiency than participants in the explicit condition, who appeared to be unable to switch efficiently between the tasks or process the tasks in parallel without disruption to motor output (Hazeltine, Ruthruff, & Remington, 2006).

Firm conclusions about the underlying reasons for the Poolton et al. (2006) findings are clouded by the possibility that motor adaptations were ongoing during the low complexity and high complexity decision-making tests. Participants were required to direct shots to a central target during the learning phase, but to the left or the right side of the table during the decision-making phase. Differential adaptation by participants in the two conditions, to the new task demands, may have taken place during the decision-making phase. Better adaptation by the implicit (analogy) learners would have hidden the disruptive effect of the high complexity decisions.

In the present experiment we addressed this possible confound by sandwiching the decision-making tests between two transfer tests that required participants to hit balls alternately to the left and right of centre. The transfer tests served as a measure of baseline transfer performance and allowed an assessment of the amount of adaptation in the two conditions during the test phase (superior performance in the second transfer test would be indicative of learning). Kinematic analysis of movement was also performed to identify some of the movement characteristics associated with implicit (analogy) learning and explicit learning and to examine the kinematic effect of producing a movement and a decision concurrently. We expected that participants in the implicit condition would show stable (or improved) motor performance and unperturbed movement kinematics when required to make concurrent low or high complexity decisions. In contrast, we expected that participants in the explicit condition would show reduced motor performance and perturbed movement kinematics (e.g., increased jerk; Maxwell et al., 2003). Implicit (analogy) learners were also expected to report less explicit (declarative) knowledge of their movements than explicit learners.

Method

Participants

Thirty-five undergraduate students (*M* age = 21.3 years, *SD* = 2.27) from the University of Hong Kong were randomly assigned to either an Analogy (*n* = 17) or an Explicit condition (*n* = 18). All participants were right-handed and had little or no table tennis experience. Participants provided informed consent and received 100 HKD (approximately 13 USD) for participation.

Apparatus

The experiment was performed on a standard table tennis table (Komann KBT-2018). At one end was a Newgy Robo-pong 2000 table tennis ball server that discharged 40 mm balls at a frequency of 30 balls/min. The balls were directed down the centre line of the table with backspin, ascending to approximately 20 cm at the table's edge. One hundred balls (50 white and 50 yellow) were placed in the ball storage hopper and mixed regularly to ensure that they were randomly dispersed. The ball server was adapted to prevent identification of ball color prior to its discharge. All participants used a Donic Waldner 500 table tennis bat. A reflective marker, attached to the distal edge of the bat, was tracked by a six camera Qualysis Medical AB motion capture system that allowed analysis of bat movement kinematics during task execution.

Below the server, six large squares (50 cm x 50 cm) were marked on the table, in two rows (Figure 1). Each square in the row furthest from the participant housed a concentric target (25 cm x 25 cm). During the learning trials, participants aimed to hit the central target and were awarded three points for hitting Zone 2. Two points were awarded for hitting Zone 5. A ball landing in any other zone received one point. In the Test Phase, the targets on the left or right of the table were used. Three points were awarded for hitting Zone 1 or Zone 3, with two points awarded for hitting Zone 4 or Zone 6 respectively. One point was awarded for hitting any other zone. Balls hit to the incorrect side of the table or out of a marked zone scored zero. To provide an example, a ball directed (correctly) to the right-hand target scored one point for hitting Zones 2, 5, 8 or 9 and scored zero for hitting Zones 1, 4 or 7.

Procedure

Participants were informed that the task was to develop an accurate topspin forehand shot. They were told that the objective of the task was to return shots, with topspin, toward Zone 2 (Figure 1). The ball rotation generated by a topspin forehand was explained and participants were asked to hold the bat using a western ‘shake hands’ grip (Sneyd, 1994). Separate instructions were provided in the two treatment conditions. Six step-by-step instructions were presented in the Explicit treatment condition (Table 1), whereas, in the Analogy condition a single analogical instruction was presented; “move the bat as if it is traveling up the side of a mountain” (Poolton et al., 2006). At no point was a topspin forehand demonstrated. Three hundred trials were completed in fifteen 20 trial blocks, over a one hour learning period. The importance of following the instructions was emphasized prior to each block of trials. If a participant failed to hit shots with topspin within a block of trials (adjudged by the experimenter) the appropriate ball rotation was again explained. No feedback was given concerning the correctness of a participant's technique. After the learning phase, a Declarative Knowledge Protocol was administered, which asked participants to report, in as much detail as possible, any movements, methods or techniques they remembered using to perform the task.

Table 1 near here

In the test phase, low and high complexity tests were sandwiched between two transfer tests. Each test consisted of two blocks of 20 trials (the two blocks were later analyzed together as one 40 trial block). In the two transfer tests, instead of hitting toward the central target, balls were hit to targets on the left (Zone 1) or the right (Zone 3) side of the table in an alternating sequence, such that the first ball was hit to the right, the second to the left, the third to the right, and so on. In the low and high complexity tests the location of the target was specified by ball color. In the low complexity test, white balls were to be hit to the right and yellow balls were to be hit to the left. Prior to motor performance, participants' ability to make correct decisions was evaluated in a 20 trial block (decision-only test); wherein, participants verbally indicated whether the ball should be hit left or right.

In the high complexity test, the ball color/target representation alternated after every two balls. For trials 1 and 2, as in the low complexity test, white balls were to be hit to the right and yellow balls to the left. In trials 3 and 4, the ball color/target representation switched, so that white balls were to be hit to the left and yellow balls to the right. Trials 5 and 6 reverted back to white-right and yellow-left. Trials 7 and 8, white-left and yellow-right, and so on. As in the low complexity test, ability to make correct decisions was evaluated by a decision-only test. On occasions when participants forgot the correct ball color sequence, the experimenter was immediately notified, and participants were asked to resume from the initial starting sequence (e.g., for the first two balls, white balls to be hit to the right-hand target).

Total score in each block of 20 trials (maximum score 60) was computed as a percentage and used as the dependent variable in the learning phase. In the test phase, the manipulation of decision complexity was examined by totaling the number of correct decisions made in the low and the high complexity tests, both when the decisions were made alone and when they accompanied a motor response. To assess motor performance in the test phase and to avoid the possibility of confounding by a decision versus motor performance trade off, we computed our dependent variable from the mean performance only on trials in which a correct decision was made.

During the high complexity test participants were asked to immediately report occasions when the sequence of the task was forgotten. It became clear, however, that participants had on occasions unwittingly forgotten the order to be followed. A string of correct responses would be followed by a series of incorrect responses, but the order of the incorrect decisions was not random. It seemed that participants inadvertently missed a ball in the sequence and continued the sequence from the next ball. As a result, the ball sequence that participants followed on these occasions was not matched to the experimental ball sequence; thus, performance scores did not always reflect task proficiency. To address this problem, we identified the ball in the sequence that the participant had missed - performance was then rescored from this point. As a result of the subjective nature of this procedure, a second rater independently rescored the number of correct decisions made in the high-complexity test. Significant correlations between the two raters in both the decision-only (ICC = .89, F (34) = 16.81, $p < .001$) and motor performance tests (ICC = .84, F (34) = 11.14, $p < .001$) confirmed the accuracy of the primary rater's scoring.

The motion capture system was used to track bat movement in the first and final block of learning and in the first 20 trials of each block in the test phase. The system operated at a sampling frequency of 60 Hz and tracked the reflective marker attached to the bat to within 1 mm of error. The relative position of the bat at each point in time was specified by x, y, and z coordinates. From the output data we extracted the three-dimensional coordinates of the marker trace for each trial. A trial was defined as the initial backward preparatory movement through the forward movement to the highest vertical point of the follow-through. From the coordinates we computed peak and mean movement speed by calculating the distance traveled in three dimensional space (in meters) at each sampled time point and dividing by unit time (i.e. 1/60 seconds). Peak and root mean square acceleration (RMSacc), and peak and root mean square jerk (RMSjerk) were calculated as the second and third time derivatives of distance, respectively. Trial-to-trial variability (standard deviation) for each of the six kinematic measures was also calculated, yielding 12 dependent variables in total. Data from seven participants (three from the Analogy condition $n = 14$: four from the Explicit condition $n = 14$) were excluded from kinematic analysis of the learning phase because either system failure or a poor quality marker trace prevented a comprehensive analysis. Four participants (one from the Analogy condition $n = 16$: three from the Explicit condition $n = 15$) were excluded from analysis of the test phase.

The Declarative Knowledge Protocols were scored by two independent raters. The raters assessed the amount of information related to the mechanics of movement (e.g. “I turned my shoulders as I struck the ball” or “I kept the bat as much as possible on a vertical plane”). An Intraclass Correlation Coefficient showed a high level of concordance between the two rater's scores (ICC = .92, F (34) = 22.51, $p < .001$). The scores from the independent raters were therefore averaged for analysis.

Results

Performance – Learning Phase

The accuracy of topspin forehand performance during learning was assessed by a Group x Block (2 x 15) ANOVA with repeated measures on the Block factor and Greenhouse-Geisser's epsilon adjustment to degrees of freedom in all cases. A main effect was shown for Block (F (8.01, 264.26) = 23.26, $p < .001$, $\eta^2 = .41$), but not for Group (F (1, 33) = .66, $p = .42$, $\eta^2 = .02$). No Group x Block interaction was evident (F (8.01, 264.26) = .74, $p = .65$, $\eta^2 = .02$). As illustrated in Figure 2, the treatment conditions appeared to have similar learning outcomes.

Kinematics – Learning Phase

The analysis of performance during the learning phase demonstrated no differential effect of instructional method; therefore, main effects of Group were not expected in any of the kinematic parameters. However, performance increased over Blocks so we expected to also see evidence of change over block in the kinematic parameters. The same rationale caused us to expect no interactions between Group and Block.

Univariate ANOVAs computed for each dependent measure demonstrated significant effects of Block for mean speed (F (1, 26) = 12.22, $p < .005$, $\eta^2 = .32$), peak speed (F (1, 26) = 20.46, $p < .001$, $\eta^2 = .44$), peak RMSacc (F (1, 26) = 5.36, $p < .05$, $\eta^2 = .17$), and trial-to-trial variability of mean RMSacc (F (1, 26) = 6.19, $p < .05$, $\eta^2 = .19$). Mean and peak speed, and peak RMSacc increased over learning; whereas trial-to-trial variability decreased. This pattern suggests that shots were made with greater force and became more consistent with practice. Although changes were not significant for other variables, they followed the same pattern (i.e. increasing mean and peak values and decreasing trial-to-trial variability).

Contrary to expectations, group effects were evident for peak RMSacc (F (1, 26) = 12.18, $p < .005$, $\eta^2 = .32$), mean RMSacc (F (1, 26) = 9.77, $p < .005$, $\eta^2 = .27$), trial-to-trial variability of peak RMSacc (F (1, 26) = 4.44, $p < .05$, $\eta^2 = .15$), peak RMSjerk (F (1, 26) = 14.80, $p < .005$, $\eta^2 = .36$), trial-to-trial variability of peak RMSjerk (F (1, 26) = 4.28, $p < .05$, $\eta^2 = .14$), mean RMSjerk (F (1, 26) = 4.44, $p < .05$, $\eta^2 = .15$), and trial-to-trial variability of mean RMSjerk (F (1, 26) = 5.94, $p < .05$, $\eta^2 = .19$). In all cases, larger values were evident for the Analogy group. No interactions between group and block were found.

Decision-only Test

A Group x Decision (2 x 2) ANOVA with repeated measures on the number of correct verbal responses made in the low- and high-complexity tests showed no main effect of Group (F (1, 33) = 1.22, $p = .28$, $\eta^2 = .04$) or interaction (F (1, 33) = .63, $p = .43$, $\eta^2 = .02$). A main effect of Decision was evident (F (1, 33) = 56.65, $p < .001$, $\eta^2 = .63$). Fewer correct decisions were made in the high complexity test (M = 81.71%) than in the low complexity test (*M* = 98.86%), corroborating the effectiveness of the complexity manipulation.

Motor Performance - Test Phase

The ability of participants to adapt to hitting the ball to the left and right side of the table rather than down its centre was assessed by a Group x Block (final 20 trials of learning vs. transfer 1) ANOVA. The analysis showed a main effect of Block only (F (1, 33) = 9.84, $p < .005$, $\eta^2 = .23$). Performance accuracy in the transfer test was lower, but the two conditions appeared to transfer to the new task demands in a similar manner.

Motor performance in the test phase was assessed by a Group x Block (2 x 4) ANOVA with repeated measures, taking percentage score per correct decision as the dependent variable. No significant effect of Group was shown (F (1, 33) = 1.49, $p = .23$, $\eta^2 = .04$); however, a main effect of Block (F (2.81, 92.64) = 4.70, $p < .01$, $\eta^2 = .13$) and an interaction (F (2.81, 92.64) = 4.30, $p < .01$, $\eta^2 = .12$) were evident. *A posteriori* analysis of simple main effects showed no effect of Block for the Analogy condition (F (2.59, 41.4) = 1.39, $p = .26$, $\eta^2 = .08$), whereas a significant effect was evident for the Explicit condition (F (2.72, 46.25) = 7.22, $p < .005$, $\eta^2 = .30$). As illustrated in Figure 2, participants in the Explicit condition showed significantly poorer performance in the high complexity test, compared to performance in the low complexity test ($p < .01$) and performance in the second transfer test ($p < .005$) respectively. Additionally, participants in the Explicit condition had superior motor performance in the low complexity test and transfer 2 than in transfer 1 (both $p < .01$), indicative of continued learning during the test phase.

Assessment of the number of correct motor responses made in the low and high complexity tests showed no main effect of Group (F (1, 33) = 2.08, p = .16, $ŋ^2$ = .06) or Group x Block interaction (F (1, 33) = .31, p = .58, $ŋ^2$ = .01); however, an effect of Block (F (1, 33) = 71.21, p < .001, $ŋ^2$ = .68) was evident. More correct decisions were made in the low complexity test (M = 94.72%) than in the high complexity test (M = 78.14%).

Kinematics - Test Phase

The performance results in the test phase allowed specific predictions to be made regarding changes in the kinematic parameters of the movements in each treatment condition. The lack of performance change in the Analogy condition suggests that an absence of changes in kinematic parameters should also be evident. Conversely, the changes in performance in the Explicit condition should be reflected by changes to key kinematic parameters, particularly during the high complexity decision test. To verify these predictions, separate univariate repeated measures analyses were conducted for each group, taking each of the 12 kinematic variables as a dependent measure.

No significant effects of Block were found in the Analogy condition (p > .05 in all cases), consistent with their performance data (Table 2a). However, significant changes were evident in several of the kinematic parameters assessed in the Explicit condition, including mean speed (F (1.84, 25.70) = 5.11, p = .01, $ŋ^2$ = .27), peak speed (F (2.67, 37.65) = 8.50, p < .001, $ŋ^2$ = .38), trial-to-trial variability of mean speed (F (2.55, 35.76) = 3.07, p < .05, $ŋ^2$ = .18), trial-to-trial variability of RMSacc (F (1.83, 25.59) = 3.64, p = .04, $ŋ^2$ = 21), and trial-to-trial variability of RMSjerk (F (2.90, 40.56) = 3.97, p = .02, $ŋ^2$ = .22). Pairwise comparisons (Bonferroni) revealed generally lower mean and peak values, and greater trial-to-trial variability during the high complexity test relative to the low complexity test and/or the first and second transfer tests, although trial-to-trial variability was also generally higher during the first transfer test, possibly due to the initial novelty of this block (Table 2b).

Tables 2a & 2b near here

Declarative Knowledge Protocol

The amount of explicit knowledge relevant to the mechanics of the movements was contrasted in the two treatment conditions using an independent samples t-test, which showed a significant difference between the two groups (t (33) = -2.68, $p < .05$, d = -.91). More knowledge was reported by participants in the Explicit condition (M = 4.67, SD = 2.10) than in the Analogy condition (M = 3.18, SD = 1.04).

Discussion

Poolton et al. (2006) showed that in a time constrained environment performance costs associated with processing both a difficult decision and an immediate motor response can be reduced if the motor task is acquired ‘implicitly’ – via analogy learning. The findings may have been confounded by adaptations during the decision-making test phase, caused by the requirement to hit to targets left or right of center, rather than centrally as in the learning phase. To overcome this problem in the current experiment, a transfer test was introduced both before and after the low- and high-complexity decision-making tests, to ascertain whether adaptation continued throughout the test phase. In addition, kinematic analysis of movement was performed.

Participants learned to hit topspin forehand shots implicitly, via presentation of a single analogical instruction or explicitly, via six step-by-step instructions. Consistent with previous findings in the explicit/implicit motor learning literature (Law, Masters, Bray, Eves, & Bardswell, 2003; Liao & Masters, 2001; Poolton et al., 2006), analogy learning resulted in reports of less movement related knowledge than explicit learning, suggesting that a smaller amount of movement information was accessible to working memory for on-line control of movement.

Fewer correct decisions were made in response to the high-complexity decision than the low complexity decision. The relative simplicity of low-complexity decisions meant that motor performance was not disrupted in either learning condition. No between condition differences were evident when a complex decision was required; however, performance was disrupted in the explicit condition, but not the analogy condition. This finding replicates the work of Poolton et al. (2006) and implies that implicit motor learning, via analogy, facilitates the processing of multiple streams of information in a manner that is associated more with the performance of experts than novices.

Analysis of the kinematic parameters showed that the movement characteristics remained constant in both conditions during the low complexity decision-making task, but that mean and peak movement speed decreased and trial-to-trial variability increased in the explicit condition, but not the analogy condition, during the high-complexity decision task. For the explicit learners, the demands associated with the task may have caused stiffening of the movements. The reason for this is unclear, although it is common for people to become anxious if they perceive themselves unable to meet the demands of a task (e.g., Cherry, 1978; McGrath, 1970), and anxiety has been shown to increase motor stiffness (van Loon, Masters, Ring, & McIntyre, 2001).

It has been proposed elsewhere (Masters & Liao, 2003) that analogies act as 'biomechanical metaphors' that encapsulate (or chunk) many of the step-by-step rules of explicit performance. Interestingly, analogy learning in the current study produced movements with higher peak acceleration, mean acceleration, peak jerk, mean jerk and trial-to-trial variability than in the explicit, step-by-step instruction condition. These findings may reflect a learning paradigm that quickly results in characteristics of expert performance. For example, Bootsma and van Wieringen (1990) reported that expert players compensate for later shot initiation by increasing the force (acceleration) applied in the shot. The greater acceleration (e.g., faster swing) evident in the analogy condition implies that movements may have been initiated later by analogy learners in an effort to give themselves more time to process the high-complexity decision before initiating the motor response. Direct comparison of the movement kinematics in each condition with those of expert performers would indicate how closely the movements reflect those of an expert.

Although our findings support the working memory explanation (Masters & Maxwell, 2004) for why implicit motor learning allows more efficient decision-making and motor performance in time constrained environments, an alternative explanation is that the modular architecture of working memory (Baddeley, 2003) allows parallel performance of the tasks without taxing the same modules. Whereas cognitively demanding decisions (Jameson et al., 2004) and manipulation of explicit information (MacMahon & Masters, 2002), occur in the central executive module of working memory, analogical instruction does not. Despite the verbal manner in which the analogy is communicated, Liao and Masters (2001) argued that it is likely to be processed as an image in the visuo-spatial sketchpad module of working memory, from where it can be directed to support movement control. Consequently, the two tasks may be processed in different modules within working memory without overreaching the capacity of working memory to process them simultaneously.

Another possibility is that analogy learners more easily switched between the two tasks than explicit learners. Poolton et al. (2006) dismissed this possibility on the grounds that the time window for task execution was unlikely to be sufficient to accommodate task switching behavior. The temporal constraints of the task in this study also suggest that task switching was not feasible. Durations between shot initiation and bat-ball contact of 370 ms have been shown to increase to approximately 399 ms when parameters of the movement must be adapted in order to hit the ball either to the left or the right side of the table (e.g., Roth, 1989). We approximated that a 450 ms time window between ball release and ball strike was available in which to execute the movement. Given that simple reaction times approximate 190 ms and escalate as the number of stimulus-response choices increase (Hick, 1952; Welford, 1980), an overlap between the two components of the task was probable and task switching is unlikely to have been an effective strategy.

In sum, our findings suggest that although analogical instructions are conveyed *explicitly* they are cognitively efficient (as defined by Moors & De Houwer, 2006), in that they demand few processing resources (Law et al., 2003; Liao & Masters, 2001; Masters & Liao, 2003; Poolton et al., 2006). As a consequence, it appears that learning by analogy installs (implicit) characteristics in the motor behavior of novices that normally are not evident in perception-action behavior until the performer is much further along the road to expertise.

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Table 1. Instructions to participants in the Analogy learning condition and the Explicit learning condition (a Cantonese translation of these instructions is available from the authors).

	Instructions
Explicit learning*	1. Keep your feet a little wider than shoulder width apart 2. Position your feet behind the table with the right foot furthest from the table 3. Move the bat backwards and down 4. Move your body weight to the front leg 5. Move your playing arm forwards and upwards 6. Keep the bat face at a vertical angle
Analogy learning	Move the bat as if it is traveling up the side of a mountain

* Instructions for the Explicit learning condition were taken from Sneyd (1994) and The Sport Council (1995).

Table 2a. Mean (SD) values of all kinematic variables during the test phase (Analogy learning).

	Transfer 1	*Low Complexity*	*High Complexity*	*Transfer 2*
Mean movement speed	2.57 (.69)	2.57 (.74)	2.45 (.63)	2.54 (.65)
Root mean square acceleration (RMSacc)	40.46 (11.27)	43.82 (18.96)	40.66 (11.53)	37.65 (11.40)
Root mean square jerk (RMSjerk)	1274.16 (355.45)	1328.14 (450.69)	1316.21 (344.00)	1172.12 (346.41)
Peak movement speed	6.49 (1.56)	6.49 (1.57)	6.16 (1.58)	6.41 (1.69)
Peak RMSacc	91.64 (24.88)	107.82 (77.81)	92.22 (24.90)	88.44 (28.04)
Peak RMSjerk	3851.64 (1000.59)	3904.82 (1295.77)	3794.70 (892.49)	3565.32 (1161.18)
Trial-to-trial variability of mean movement speed	.32 (.11)	.31 (.11)	.35 (.13)	.41 (.17)
Trial-to-trial variability of RMSacc	6.57 (2.43)	7.19 (6.30)	7.26 (2.99)	6.79 (2.89)
Trial-to-trial variability of RMSjerk	294.70 (97.71)	354.91 (395.05)	329.34 (126.15)	288.48 (111.18)
Trial-to-trial variability of peak movement speed	.66 (.26)	.72 (.48)	.72 (.31)	.71 (.27)
Trial-to-trial variability of peak RMSacc	20.72 (7.76)	25.53 (35.01)	20.81 (9.48)	19.58 (8.30)
Trial-to-trial variability of peak RMSjerk	1244.42 (441.75)	1539.76 (1882.26)	1229.70 (533.36)	1149.69 (512.91)

No significant differences between blocks for any measure at $p < .05$; distance measured in meters and time in seconds.

Table 2b. Mean (*SD*) values of all kinematic variables during the test phase (Explicit learning).

	Transfer 1	*Low Complexity*	*High Complexity*	*Transfer 2*
Mean movement speed	2.41 (.56)^{a}	2.22 (.48)^{a,b}	2.16 (.44)^{b}	2.36 (.51)^{a}
Root mean square acceleration (RMSacc)	32.98 (10.68)^{a}	30.52 (8.43)^{a}	30.08 (7.76)^{a}	30.15 (6.90)^{a}
Root mean square jerk (RMSjerk)	1016.36 (330.30)^{a}	903.70 (226.88)^{a}	923.32 (278.77)^{a}	931.31 (179.08)^{a}
Peak movement speed	6.21 (1.04)^{a}	5.99 (1.08)^{a}	5.51 (.79)^{b}	6.00 (.92)^{a}
Peak RMSacc	74.43 (19.86)^{a}	70.67 (19.50)^{a}	68.61 (13.85)^{a}	70.90 (15.05)^{a}
Peak RMSjerk	3060.31 (770.36)^{a}	2859.05 (648.49)^{a}	2799.31 (557.88)^{a}	2921.74 (555.79)^{a}
Trial-to-trial variability of mean movement speed	.36 (.14)^{a}	.28 (.09)^{a}	.33 (.12)^{a}	.26 (.09)^{a}
Trial-to-trial variability of RMSacc	5.64 (2.83)^{a,b}	3.94 (1.51)^{a}	5.32 (1.79)^{b}	4.62 (1.06)^{a,b}
Trial-to-trial variability of RMSjerk	225.21 (99.57)^{a,b}	166.46 (62.70)^{a}	238.77 (101.55)^{b}	212.12 (70.56)^{a,b}
Trial-to-trial variability of peak movement speed	.57 (.36)^{a}	.47 (.14)^{a}	.79 (.64)^{a}	.53 (.20)^{a}
Trial-to-trial variability of peak RMSacc	15.53 (6.58)^{a}	12.47 (3.94)^{a}	18.52 (11.05)^{a}	15.99 (5.40)^{a}
Trial-to-trial variability of peak RMSjerk	887.42 (344.58)^{a}	818.01 (371.35)^{a}	1108.23 (539.53)^{a}	872.47 (308.72)^{a}

Shared superscript denotes no significant differences at $p < .05$; distance measured in meters and time in seconds.

Captions

Figure 1. Target areas - Zone 2 was targeted during the learning phase, whereas, Zones 1 and 3 were the targeted during the test phase.

Figure 2. Motor performance (hitting accuracy) in the Analogy condition and in the Explicit condition during the learning phase and the test phase (T1 = transfer test 1; L-C = low-complexity decision test; H-C = high-complexity decision test; T2 = transfer test 2).

Figure 1

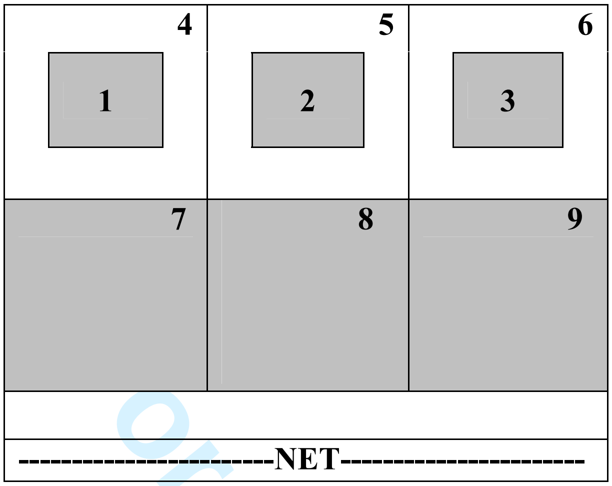
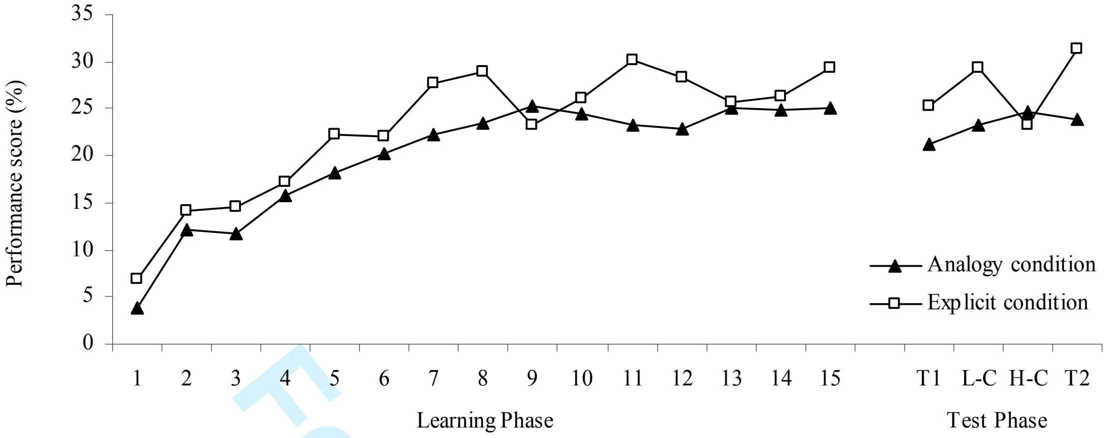


Figure 2


35
30
25
20
15
10
5
0
Performance score (%)
Analogy condition
Explicit condition
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
T1
L-C
H-C
T2
Learning Phase
Test Phase