The influence of robotic guidance on error detection and correction mechanisms

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ABSTRACT

New technologies have expanded the available methods to help individuals learn or re-learn motor skills. Despite equivocal evidence for the impact of robotic guidance for motor skill acquisition (Marchal-Crespo, McHughen, Cramer, & Reinkensmeyer, 2010), we have recently shown that robotic guidance mixed with unassisted practice can significantly improve the learning of a golf putting task (Bested & Tremblay, 2018). To understand the mechanisms associated with this new mixed approach (i.e., unassisted and robot-guided practice) for the learning of a golf putting task, the current study aimed to determine if such mixed practice extends to one's ability to detect errors. Participants completed a pre-test, an acquisition phase, as well as immediate, delayed (24-h), and transfer post-tests. During the pre-test, kinematic data from the putter was converted into highly accurate, consistent, and smooth trajectories delivered by a robot arm. During acquisition, 2 groups performed putts towards 3 different targets with robotic guidance on either 0% or 50% of acquisition trials. Only the 50% guidance group significantly reduced ball endpoint distance and variability, as well as ball endpoint error estimations, between the pre-test and the post-tests (i.e., immediate retention, 24-h retention, and 24-h transfer). The current study showed that allowing one to experience both robotic guidance and unassisted (i.e., errorful) performances enhances one's ability to detect errors, which can explain the beneficial motor learning effects of a mixed practice schedule.

1. Introduction

Past research has focused on the understanding and development of the best training protocols to improve motor learning (Kümmel, Kramer, & Gruber, 2014; Proteau, Marteniuk, & Lévesque, 1992; Williams & Carnahan, 2017; Williams, Tremblay, & Carnahan, 2016; Wulf, Shea, & Whitacre, 1998). With the advancement of technology, robotic devices have been used to help teach novel movements by guiding participants through an "ideal" or "perfect" trajectory (i.e., robotic guidance: e.g., Kümmel et al., 2014). Although prior investigations of robotic guidance have produced marginally positive findings, recent studies have varied how robotic guidance was employed (e.g., Bested & Tremblay, 2018; Kümmel et al., 2014; Manson et al., 2014; Marchal-Crespo, McHughen, Cramer, & Reinkensmeyer, 2010; Marchal-Crespo, Schneider, Jaeger, & Riener, 2014; Marchal-Crespo & Reinkensmeyer, 2008; Williams & Carnahan, 2017; Williams et al., 2016). Notably, these results may have been grounded in improvements of error-detection mechanisms.

The rationale for conducting the current study was partially rooted in prior investigations on observational learning. Observational learning has been identified as a useful tool for motor skill acquisition and thought to utilize the same mechanisms involved with physical practice (e.g., Cisek & Kalaska, 2004; Dushanova & Donoghue, 2010). Critically, mixed observation, which is the observation of both an expert model and novice model, has been found to be more beneficial for the learning of a complex task, compared to only observing a novice model or expert model alone (e.g., Rohbanfard & Proteau, 2011). As well, mixed observation with physical practice yields improved retention of a sequential motor task, as compared to experiencing only a novice or expert model with physical practice (Andrieux & Proteau, 2013). From these results, Andrieux and Proteau (2013) suggested that by allowing participants to observe both expert and novice models while experiencing their own performance, errors became more prominent or salient to participants. As a result, participants were able to better detect and correct errors accordingly. Following up on their own work, Andrieux and Proteau (2014) investigated if mixed observation specifically improved the participant's error detection mechanisms. As expected, participants that observed both an expert and novice model were better at estimating their error than participants who observed other regiments of observation. This corresponded with the previous investigations of the development of an error detection mechanism in participants that used observation only during acquisition and as a result of physical practice (Blandin & Proteau, 2000; Schmidt & White, 1972). Overall, observing both an expert and a novice model while also physically performing the task-to-be-learned has resulted in an improvement in error estimation/detection and learning of the task being performed (Andrieux & Proteau, 2013, 2014; Blandin & Proteau, 2000; Schmidt & White, 1972). However, it is not known if the performance improvements arising from the incorporation of robotic guidance with unassisted practice will also yield better error detection processes.

Bested and Tremblay (2018: see also Bested, Manson, & Tremblay, submitted) tested if robotic guidance could help inexperienced golfers learn a putting task. Based on the Manson et al. (2014) upper-limb guidance study, a variable practice schedule was employed wherein multiple targets were presented during acquisition for all groups (e.g., Shea & Kohl, 1990, 1991; Tremblay, Welsh, & Elliott, 2001). One group solely practiced without robotic guidance (i.e., unassisted), another group practiced solely with robotic guidance, and a third group alternated between unassisted and guided trials throughout acquisition (i.e., mixed practice). During an immediate and a 24-h retention test, the only group that improved both their mean and the standard deviation of the ball endpoint locations was the group that incorporated mixed practice (i.e., unassisted and robot-guided trials). Bested and Tremblay (2018) hypothesized that participants experienced the perfect swing (i.e., robotic guidance trials) as well as their own errors (i.e., no guidance trials), which allowed them to learn the task most effectively. More specifically, it is possible that mixing robotic guidance with unassisted practice (i.e., guidance and no guidance trials) led to more salient error detection processes relative to only practicing with the typical errors of unassisted practice. This would be the case because the reference-of-correctness (see Adams, 1971) provided during robotic guidance would be more accurate than that of unassisted practice conditions (see below). The current study therefore aimed to test the hypothesis that the incorporation of robotic guidance trials enhances performance and error detection processes to a greater extent than unassisted practice.

The feedback from robotic guidance may improve performance because it helps establish an 'ideal or perfect' reference-of-correctness (e.g., recall and recognition schema: Schmidt, 1975). However, it seems that for these improvements to take place, and for learning to occur, one cannot strictly rely on robotic guidance during acquisition. That is, once it is removed, performance may deteriorate (e.g., guidance hypothesis: Schmidt, Young, Swinnen, & Shapiro, 1989; Schmidt, 1991). Although experiencing the ideal reference-of-correctness through robotic guidance is important, experiencing past performances as well as errors is important in developing the recall and recognition schema (Schmidt, 1975). This may explain why when Bested and Tremblay (2018) employed a robotic guidance paradigm, only their 50% guidance group improved in the main performance measures (i.e., mean and standard deviation of ball endpoint locations). This 50% guidance group experienced both the ideal reference-of-correctness as well as their own errorful performance potentially not only developing their recall and recognition schema but also improving their ability to detect and correct errors accordingly.

In the current study, participants performed a golf putting task focusing primarily on distance control (i.e., primary movement axis – Y) as in the study by Bested and Tremblay (2018). Participants were separated into two separate groups in which they were either unassisted during training or trained with robotic guidance on 50% of the trials (i.e., mixed practice). Performance and learning were evaluated based on where the ball stopped on the green (i.e., ball endpoint location) during different testing phases. Additionally, error estimation was assessed by having participants estimate where they thought their ball landed. Overall, it was hypothesized that incorporating robotic guidance with unassisted practice (i.e., mixed practice) would enhance both the performance and learning of a putting task as well as enhance the underlying error estimation processes.

2. Methods

2.1. Participants

Thirty-four neurologically intact participants were recruited from the University of Toronto community (17 males and 17 females; M = 26.2 yrs, range = 18–47 yrs). All participants had normal or to corrected-to-normal vision and were self-declared right-hand dominant. Each participant signed a consent form before taking part and the study was approved by the Research Ethics Board at the University of Toronto. For participating in the study participants received payment of $10/h for time in testing.

2.2. Apparatus

Participants performed the golf putting task on a custom-built putting green (BirdieBall Inc., Wheat Ridge, CO, USA) measuring 488 cm long × 122 cm wide with three custom-built circular Light-Emitting Diode (LED) targets (see Fig. 1). The putting green was laid on the floor in a 6 m by 5 m room. The LED targets represented a golf hole measuring 10.8 cm in diameter constructed with 8 bright white circular LED's (i.e., 2 mm in diameter) per target. The three targets were inserted into the underside of the putting green so that they were unseen when not illuminated. To ensure that the targets were of perceivably different amplitudes (re.: Weber's Law; see Gescheider, 1997), they were positioned at distances of 192, 213, and 234 cm (i.e., 213 ± 10% of 213) from the home position (i.e., from center to center). All three targets and the home position were positioned 52 cm from the rightmost edge of the putting green. An enclosure (L: 193 cm × W: 208 cm × H: 202 cm) was used to protect participants from the Selective Compliant Assembly Robot Arm used for physical guidance trials (SCARA; Epson E2L853, Seiko Epson Corp., Owa, Suwa, Nagano, JAPAN). The robot arm can move in four degrees of freedom and replicate movements with a 0.02 mm spatial repeatability. An opening in the protective enclosure (H: 80 cm high × W: 208 cm) allowed the functional end of the robot effector/ arm to be positioned directly in line with the home position on the floor. As a result of the robot extending outside of the enclosure, an extension of the enclosure was built to ensure participants could not come in direct contact with the robot (L: 48 cm × W: 208 cm). To perform each golf putt, a Titleist Scotty Cameron Studio Select Newport 1.5 putter was used (Titleist Inc., Fairhaven, MA, USA: weighing 509 g) and a Nike SFT golf ball (Nike Inc., Beaverton, OR, USA). During robotic guidance trials a second Titleist Scotty Cameron Studio Select Newport 1.5 putter (Titleist Inc., Fairhaven, MA, USA) was connected to the robot using a custom-built connector (see Fig. 1). A Surface Pro tablet and stylus (Surface Pro, Microsoft CO., Washington, DC, USA) was also used with a custom Matlab script (The MathWorks Inc., Natick, MA, USA). Participants used the tablet and stylus to estimate where they thought their ball stopped on the green (see below for more details). The participants were outfitted with liquid-crystal goggles (Translucent Technologies Inc., Toronto, ON, CAN: Milgram, 1987), which were used to manipulate the participants entire visual field (see below).

Fig. 1. 3D rendering of the experimental set-up. Kinematic data of the putter was recorded by using an Optotrak 3D motion capture system, which was mounted on a custom-built stand on the right side of the putting green. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.3. Trajectory formation

Three trajectories unique to each participant (i.e., made for each golf hole) were programmed into the robot as in Bested and Tremblay (2018: see also Bested et al., submitted). These trajectories were based on each participants' Pre-Test three-dimensional putting trajectories which were recorded and sampled at 250 Hz using an infrared emitting diode (IRED) secured to the inside-front edge of the putter. The IRED on the putter head was monitored by an Optotrak Certus system (Northern Digital Inc., Waterloo, ON, Canada). The start and the end of both the backstroke and follow through of the golf putt were identified when the putting head IRED velocity twice rose above and then fell below 30 mm/s for 3 consecutive samples. The golf putting trajectories were first averaged over fifteen trials and then adjusted according to previous studies (Bested & Tremblay, 2018; Bested et al., submitted; Manson et al., 2014). The adjustments included filtering the trajectories using a polynomial fit function with a custom Matlab (The MathWorks Inc., Natick, MA, USA) script making the ideal smoothed-out trajectory for each participant individually. To ensure perfect contact with the ball was made, the secondary movement axis (i.e., X-axis) was constrained in that participants putting strokes were fitted to a constant X. Once the first trajectory was made for target 2 (i.e., Pre-Test target) the other two trajectories were scaled in the Y axis (i.e., primary movement axis: putt amplitude) by ± 10% to shorten or lengthen the putts for target 1 or target 3 accordingly. This is in line with previous literature identifying that participants golf putting trajectories increase in amplitude depending on the distance of the golf putt (e.g., Delay, Nougier, Orliaguet, & Coello, 1997; Sim & Kim, 2010), To ensure that successful guidance putts were completed, the peak velocity and peak acceleration values were scaled for each trajectory. The robot arm was controlled by using a custom SPEL + program (Seiko Epson Corp., Suwa, Nagano, JAPAN) interfacing with Matlab (The MathWorks Inc., Natick, MA, USA) to control the other experimental procedures.

2.4. Task and procedures

Participants were required to perform golf putts to three different LED targets. Each participant was pseudo-randomly assigned to one of two groups (i.e., no guidance group [NG] and 50% guidance group [50-G]), with a limitation of yielding an unequal number of male and female participants in each group. The NG group was composed of 17 participants (i.e., 9 males and 8 females) while the 50-G group was composed of 17 participants (i.e., 8 males and 9 females). Participants were instructed to try have the ball finish its trajectory on the middle of a prescribed target. On each trial, the home position and a single target were presented. Before putting the golf ball, participants were instructed on how to hold the putter with a standard overlapping putting-grip as well as to stand with their feet shoulder width apart with the ball in the center of their stance. Participants were then asked to place the putter behind the golf ball as closely as possible aligning the middle of the putter head with the middle of the golf ball. Once aligned, participants were then asked to direct their focus on the target prior to the beginning of each putt.

To signal the beginning of a trial, a double beep generated by a piezo-electric buzzer (Mallory Sonalert Products Inc.: Model SC628, tone frequency of 2900 Hz) sounded. Following this auditory cue, participants were asked to shift their focus onto the golf ball and prepare to execute the golf putt to the displayed target. After a 2-s delay, a third beep sounded instructing participants to initiate their putt. Participants were given 3 s to complete their putt (i.e., backstroke and follow through) before a final 4th beep sounded signaling the end of the trial.

The experiment consisted of five phases: Pre-Test, Acquisition, Immediate-Retention (Imm-Ret: i.e., following acquisition), Delayed-Retention (Del-Ret: i.e., 24 h following acquisition), and a Transfer testing phase (Del-Tran: i.e., 24 h following acquisition and the Del-Ret testing phase, participants putt with a different putter: Nike Ignite 005 Putter [Nike Inc., Beaverton, OR, USA] that was shorter by 5 cm, had a larger putter head, and was modified to be 5% heavier weighing 534 g). Participants performed 5 familiarization trials to the 2nd target to become accustomed to the task requirements prior to completing the Pre-Test to the same target for 15 trials. During both the familiarization and the Pre-Test, no visual feedback of the target was given (i.e., 1 s following the trial auditory pre-cue, the target disappeared). Also, during the Pre-Test, Imm-Ret, and Del-Ret phases, vision was occluded immediately following ball impact. That is, once the putter exceeded the start position by 2 cm, the liquid crystal goggles turned from transparent to translucent. This effectively removed vision of the entire visual field and ensured that participants had to estimate where their ball stopped on the green. After, the ball endpoint location was collected, the ball was removed, and vision was re-instated by the experimenter. Participants were then asked to estimate their ball endpoint location using a depiction of the golf green on the tablet. Specifically, with a stylus, participants were asked to touch on the screen where they believed their ball had stopped and once done so were asked to click save.

The acquisition procedures with both experimental groups were completed in accordance with Bested and Tremblay (2018). That is, the first group was not guided by the robotic arm during the acquisition trials (i.e., no guidance group [NG]) and the second group was guided by the robotic arm for half of the acquisition trials (i.e., 50% guidance group [50-G]). Participants in the robotic guidance group performed an additional 5 familiarization trials to get acquainted with the robotic guidance although this was done with a putt trajectory that was not their own. When participants were performing robotic guidance trials they were instructed to "focus on the position of the backswing and to try their best to reproduce the velocity or speed that the robot produced" and to "actively follow the robot and were told that if this was not done successfully then this would reduce the accuracy of the golf putt being performed by slowing down the robot or speeding it up accordingly". During acquisition, participants putt to the three targets that were each randomly presented one every three trials for a total 120 trials (i.e., 40 trials for each target). Also, the target did not disappear and participants did not wear the liquid crystal goggles so that participants had visual feedback of where the ball ended in relation to the target. For the 50-G group, participants alternated between robotic guidance trials for 12 trials in a row followed by 12 no guidance trials until acquisition was completed (i.e., mixed guidance). Participants always started acquisition with robotic guidance and ended with no guidance.

Prior to the commencement of the testing phase, participants performed 5 additional familiarization trials. Importantly as in the Pre-Test, these familiarization trials were executed with the goggle always transparent to allow participants to adjust to the disappearance of the target. Following these familiarization trials 15 experimental trials were performed to the 2nd target (i.e., with the goggles turning translucent after ball contact: Imm-Ret). Twenty-four hours later, participants performed again 20 trials to the 2nd target with the same putter (i.e., 5 familiarization and 15 experimental trials: Del-Ret). As well, participants performed another 15 experimental trials to the 2nd target with the new putter.

2.5. Data analyses

Performance data (i.e., ball endpoint location) was recorded with the use of a custom grid system. The grid consisted of 30 cm × 30 cm squares starting from the home position where the ball was placed for each putt (positive on the Y-axis: see Fig. 1). The secondary movement axis (i.e., X-axis) started from the left side of the putting green. The large grid ball endpoint location was recorded in MatLab and stored for analyses. To determine the specific location of where the ball stopped within the identified square, photos were taken of the ball location within each square using a custom-built camera holder. Each picture was uploaded and a custom Matlab script determined the exact position of the ball within the specified square. This procedure generated the exact location of the center of the ball on the putting green, to the nearest millimeter.

Performance measures of the 2nd target consisted of variable error in the primary movement axis (VEY) as well as the ball endpoint location in the primary movement axis (EndY) respectively. The secondary movement axis was not investigated in the current study as a result of the task focusing on distance control (i.e., primary movement axis – Y). The secondary movement axis was also not investigated because of the task being controlled in the secondary movement axis (i.e., constant X used for the robot trajectories).

Error detection measures of the 2nd target consisted of absolute error estimation (i.e., Absolute [Estimation of ball location – Actual ball location]) in the primary movement axis (AE EstY) as well as the variable error estimation in the primary movement axis (VE EstY) respectively.

The primary analyses of interest were separate 2 Group (i.e., NG and 50-G) × 4 Phase (i.e., Pre-Test, Imm-Ret, Del-Ret, Del-Tran) mixed model ANOVAs, with group as a between-subjects factor and phase as a within-subjects factor. Prior to the completion of the ANOVAs Levene's Test of Equality of Variances was run to ensure that the variance across groups (i.e., between groups) were comparable, which led to different post-hoc contrasts if the Levene's test was violated or not.

If the Levene's test was not violated, the main ANOVAs were conducted. Due to the theoretical relevance of potential differences both within and between groups, the interactions between Group × Phase were broken down using Tukey's HSD post-hoc tests ($p < .05$). Mauchly's Test of Sphericity was used to ensure that the variances of the differences (i.e., within groups) were comparable. If this assumption was violated, the Greenhouse-Geisser correction was applied.

In contrast, if Levene's Test was violated, independent sample t-tests were conducted between groups with the correction of equal variances not assumed. Within groups, paired sample t-tests were conducted and used with a Bonferroni correction in substitution of the mixed model ANOVA. Cohen's d_z was also calculated to measure the strength of the effect of the acquisition phase for the difference between the Pre-Test to the Imm-Ret, Del-Ret, and Del-Tran tests (Lakens, 2013).

Means and between-subject *SDs* are reported in Table 1. To be as brief as possible, only significant effects are reported. Following data collection, three (3) participants were removed from each group. Five of these participants were deemed outliers because their mean scores were greater than 2.5 standard deviations above the group's mean and one participant was removed due to recording errors. This resulted in 14 participants in each group.

Table 1
Means and between subject SDs for the performance measures and error detection measures for both groups: No Guidance (NG) and 50% Guidance (50-G) as a function of experimental phase (Pre-Test, Immediate-Retention [Imm-Ret], Delayed-Retention [Del-Ret], and Transfer Test [Del-Tran]).

	NG				50-G			
	Pre-Test	Imm-Ret	Del-Ret	Del-Tran	Pre-Ret	Imm-Ret	Del-Ret	Del-Tran
EndY (cm)	274 (62)	247 (26)	255 (36)	223 (40)	255 (45)	230 (21)	216 (23)	191 (28)
VEY (cm)	60.3 (19)	55.0 (19)	50.4 (16)	43.8 (21)	61.1 (25)	42.7 (15)	34.1 (13)	31.3 (15)
AE EstY (cm)	69.2 (39)	49.7 (22)	50.1 (26)	48.4 (26)	58.5 (25)	40.3 (16)	32.4 (8)	36.8 (16)
VE EstY (cm)	53.0 (19)	48.5 (17)	43.8 (18)	43.6 (22)	53.9 (22)	40.1 (17)	31.3 (11)	32.6 (17)

Note. EndY = ball endpoint in the primary movement axis, VEY = variable error in the primary movement axis, AE EstY = absolute constant estimation error in the primary movement axis, and VE EstY = absolute variable estimation error in the primary movement axis.

3. Results

3.1. Performance measures

For the analysis of EndY, Mauchly's test indicated that the assumption of sphericity had been violated, $X^2(5) = 39.0, p = .000$. As a result of this, the Greenhouse-Geisser correction was applied. Analysis of EndY yielded a significant main effect of Phase, $F(1.7, 44.0) = 14.9$, $p < .001$, $\eta_p^2 = 0.365$, and a significant main effect of Group, $F(1, 26) = 7.9$, $p = .009$, $\eta_p^2 = 0.234$. The Phase × Group interaction was not significant, $F(1.7, 44.0) = 0.689$, $p = .484$, $\eta_p^2 = 0.026$. Pre-planned post-hoc analyses (HSD = 51.4 cm) tested for the effect of Phase across groups. Only the 50-G group significantly reduced their ball endpoint amplitude between the Pre-Test (M = 255 cm) and the Del-Tran (M = 191 cm, $d_z = 1.23$) testing phases.

Analysis of VEY yielded a significant main effect of Phase, $F(3, 78) = 14.4$, $p < .001$, $\eta_p^2 = 0.356$, and a non-significant main effect of Group that approached statistical significance, $F(1, 26) = 3.9$, $p = .059$, $\eta_p^2 = 0.130$. The Phase × Group interaction was not significant, $F(3, 78) = 1.976, p = .124$, $\eta_p^2 = 0.071$. Pre-planned post-hoc analyses (HSD = 16.6 cm) clarified that participants in the NG group reduced their ball endpoint variability from the Pre-Test (M = 60.3 cm) to the Del-Tran (M = 43.8 cm, $d_z = 0.92$). Additionally, participants in the 50-G group exhibited a reduction in VEY from the Pre-Test (M = 61.1 cm) to the Imm-Ret (M = 42.7 cm, $d_z = 0.81$), Del-Ret (M = 34.1 cm, $d_z = 1.00$), and Del-Tran (M = 31.3 cm, $d_z = 1.07$) testing phases (see Fig. 2).

3.2. Error detection measures

The AE EstY results for the Del-Ret testing phase violated the Levene's Test of Equality of Error Variances, $F(1, 26) = 22.864$,
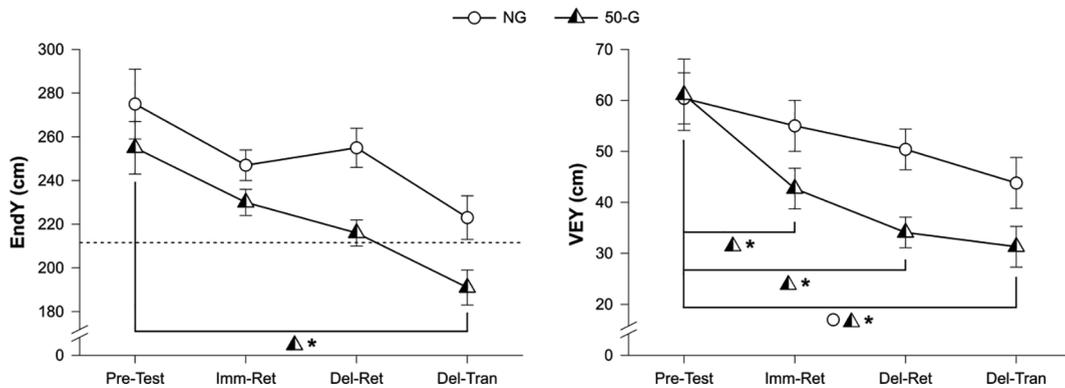

Fig. 2. Left: Ball endpoint location in the primary movement axis (EndY: dotted line represents middle of target location at 213 cm), Right: Variable error in the primary movement axis (SDY) for both groups (i.e., NG and 50-G) across each testing phase (i.e., Pre-Test, Imm-Ret, Del-Ret, and Del-Tran). Note. Within group differences are reported with a (∗), while the corresponding group is identified by their symbol (◯ = NG and ▲ = 50-G).
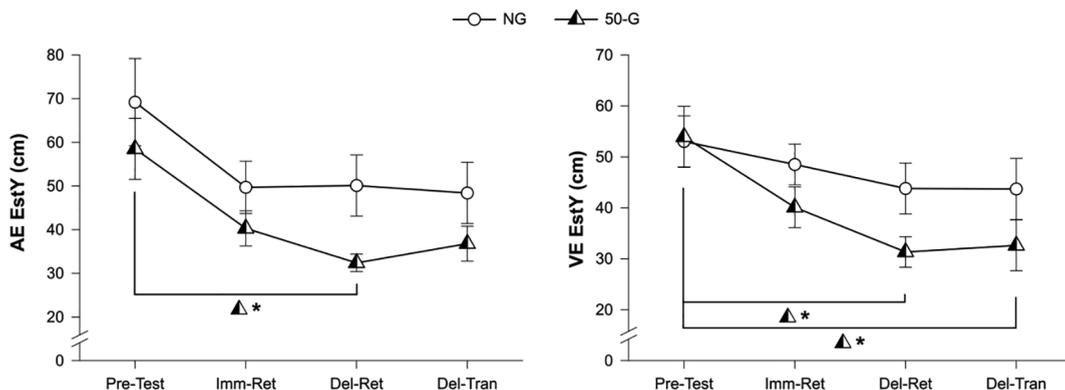

Fig. 3. Left: Absolute error estimation in the primary movement axis (AE EstY), Right: Absolute variable error estimation in the primary movement axis (VE EstY) for both groups (i.e., NG and 50-G) across each testing phase (i.e., Pre-Test, Imm-Ret, Del-Ret, and Del-Tran). Note. Within group differences are reported with a (∗), while the corresponding group is identified by their symbol (◯ = NG and ▲ = 50-G).

$p < .001$. As a result, a Bonferroni correction (i.e., $\alpha_{altered} = 0.05/9 = 0.006$) was applied to the 9 t-tests conducted on these results.[1] A significant difference for the 50-G group between the Pre-Test (M = 58.5 cm) and the Del-Ret (M = 32.4 cm, $d_z = 1.01$) testing phases, $t(13) = 3.79$, p = 0.002 was identified.

Analysis of VE EstY yielded a significant main effect of Phase, $F(3, 78) = 7.8$, $p < .001$, $\eta_p^2 = 0.231$ and a non-significant Phase × Group interaction, $F(3, 78) = 1.284$, $p = .286$, $\eta_p^2 = 0.047$. Pre-planned post-hoc analyses (HSD = 16.5 cm) clarified the main effect of Phase for the 50-G group, who exhibited a reduction in VE EstY from the Pre-Test (M = 53.9 cm) relative to the Del-Ret (M = 31.3 cm, $d_z = 0.93$), and the Del-Tran (M = 32.6 cm, $d_z = 0.87$) testing phases (see Fig. 3).

4. Discussion

The current experiment aimed to investigate the influence that trials with robotic guidance and no guidance (i.e., mixed practice) has on the development of error detection mechanisms during a golf putting task. The current investigation largely replicated the results from Bested and Tremblay (2018: see also Bested et al., submitted) and supported our hypothesis as participants exposed to mixed practice (i.e., 50-G group) performed the task optimally (i.e., on average, stopping the ball on the hole, Del-Ret = 216 cm) and did so with more consistency (i.e., reduction in variable error: see Fig. 2) than the no guidance (NG) group. More relevant to the current study, mixed practice also improved one's ability to detect and correct errors as hypothesized. Indeed, the 50-G group improved in their ability to estimate their ball endpoints (i.e., reduction in AE EstY) and mirrored the improved consistency (i.e., reduction in VE EstY) following training. Interpreting these results, it seems that mixed practice allows participants to experience the ideal reference-of-correctness while also experiencing errorful performance. Combining these two components during training, enhances one's ability to detect and as a result correct their errors accordingly.

Replicating the performance results of Bested and Tremblay (2018) as hypothesized, the 50-G group was the only group to significantly reduce their ball endpoint location (EndY) learning the task. The current investigation yielded a decrease in variable error for the primary movement axis (i.e., Y). Although an improvement in variable error in the primary movement axis (i.e., Y) was observed from the Pre-Test to the Imm-Ret testing phase, as in Bested and Tremblay (2018), participants also maintained this improvement 24 h following training in the Del-Ret and Del-Tran testing phases. This further supported the main hypothesis in that mixed practice (i.e., 50-G group) would enhance the learning of the task. Consistent with our previous work, the no guidance (NG) group did not exhibit an improvement in their average ball endpoint location in the Imm- and Del-Ret testing phases and only exhibited improvement until the Del-Tran testing phase in the current investigation. Thus, to improve task performance in this difficult putting task, participants required experience with the ideal reference-of-correctness through robotic guidance as well as their own errors through no guidance trials (e.g., Schmidt, 1975). However, it is important to note that although this study did replicate improvements in performance consistency, the current investigation eliminated visual information on ball contact. The lack of visual feedback during the testing phases can explain these differences. Indeed, visual feedback was provided in our previous work, which could be helpful for participants to correct their ball endpoint location on a trial-by-trial basis. This visual feedback likely enhanced error detection and correction mechanisms yielding better endpoint performance (e.g., Adams & Goetz, 1973).

The current results also supported our second hypothesis that participants would improve their ability to detect errors as a result of performing the task with mixed practice. That is, only the 50-G group exhibited significant improvements in error estimation (i.e., AE EstY & VE EstY). The studies conducted by Andrieux and Proteau (2013, 2014) identified that having mixed observation (i.e., mixed practice) with physical practice, induced improved retention of the task being performed and improved participants' ability to estimate their own performance (Andrieux & Proteau, 2013, 2014). The current investigation has expanded on these results demonstrating that the rationale behind mixed observation can also be applied to mixed practice. That is, experiencing both expert (i.e., robotic guidance trials) and novice (i.e., errorful) performance may enhance one's ability to detect errors accordingly resulting in errors becoming more salient to participants. Further, during mixed practice, the information provided during robotic guidance trials allows participants to develop a reference-of-correctness (e.g., recall and recognition schema: Schmidt, 1975) needed to improve one's performance. Although developing or experiencing this reference-of-correctness is essential for learning and improvements to take place, learning cannot occur without experiencing past performances as well as errors, developing the recall and recognition schema (i.e., error detection mechanism: Schmidt, 1975). This may explain the current results in this difficult task as only the 50% guidance group experienced both the ideal reference-of-correctness as well as their own errorful performance. Whereas the no guidance group would not have been able to experience what an ideal performance was as frequently and thus not being able to develop their recall and recognition schemas (i.e., error detection mechanism) to the same extent that the 50-G group was able to. This developed error detection mechanism allows participants to determine when errors occur and correct that error resulting in an improvement in performance as demonstrated (Blandin & Proteau, 2000; Schmidt & White, 1972).

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[1] Had the ANOVA analysis been completed on AE EstY, Mauchly's test indicated that the assumption of sphericity had been violated, $X^2(5) = 14.7$, $p = .012$. As a result of this, the Greenhouse-Geisser correction was applied. Analysis of AE EstY yielded a significant main effect of Phase, $F(2.2, 56.4) = 9.5$, $p = .000$, $\eta_p^2 = 0.267$ and a non-significant Phase × Group interaction, $F(2.2, 56.4) = 0.285$, $p = .770$, $\eta_p^2 = 0.011$. Pre-planned post-hoc analyses (HSD = 25.5 cm) clarified the main effect of Phase for the 50-G group, which reduced the absolute estimation error from the Pre-Test (M = 58.5 cm) to the Del-Ret test (M = 32.4 cm, $d_z = 1.01$), in agreement with the main analysis.

5. Conclusions

When learning a sequential motor skill, one must develop the appropriate error detection/ correction mechanisms for learning and improvement of the task to take place (Schmidt, 1975). Recently, Bested and Tremblay (2018) identified that for robotic guidance to be effective in teaching a novel golf putting task, participants need to experience errorful performance (i.e., no guidance trials). This was in line with results from Andrieux and Proteau (2013, 2014) as experiencing both expert as well as novice performance improved participants learning of the task and their ability to detect errors accordingly. Overall, the current study demonstrated that robotic guidance (i.e., expert performance) employed with unassisted trials (i.e., novice/errorful performance) improves the learning of a complex task. This improvement in learning can be explained by the creation of an ideal reference-of-correctness (Schmidt, 1975) as well as errorful performance used to improve one's error detection mechanisms, thus improving the learning and performance of the task being performed.

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Declaration of interest

Declaration of interest: none.

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