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Assessing the validity of an online assessment of motor learning

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ASSESSING THE VALIDITY OF AN ONLINE ASSESSMENT OF MOTOR
LEARNING

By

Alexandra T. Watral

A THESIS

Submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

In Applied Cognitive Science and Human Factors

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This thesis has been approved in partial fulfillment of the requirements for the Degree of MASTER OF SCIENCE in Applied Cognitive Science and Human Factors.

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Abstract

To understand motor learning we must observe improvements in the performance of a motor behavior over time. Current laboratory approaches to measuring motor learning are not accessible to all populations, and this lack of accessibility limits the ability of researchers to gain information about developmental processes and medical conditions that impact motor control. To date, there are a handful of portable motor learning tools that use devices such as smartphones and tablets but very few fully remote options. We have created a web-based application to assess visuomotor adaptation, a gold standard approach to studying motor learning, in a remote setting. The overarching goal of this study was to provide evidence that a web-based application is a valid way to assess motor learning in healthy younger and older adults. Younger adults (n=24) and older adults (n=19) participated in this study. Each participant met with a researcher via Zoom and shared their screen while performing the visuomotor rotation (VMR) task and a cognitive battery. Data from the application was then compared to data previously collected using traditional laboratory equipment. Results show that the online application produced similar learning curves compared to the laboratory task. Expected age differences were not seen using the application, however. Surprisingly, older adults performed better using the application than in the laboratory while younger adults performed the same across platforms. Also, our cognitive measures were not found to be associated with learning in the application version of the VMR task. Our data show that this application can be used in research with results that are similar to those acquired in a laboratory setting with the benefit of the application improving accessibility to broader populations.

1 Introduction

To learn a new motor skill we acquire the capability to produce novel movements and then refine their proficiency with continued practice. To understand this learning process we must observe improvements in the performance of a motor behavior over time. Most studies of motor learning require participants to make novel movements in a laboratory environment while the experimenter tracks their progress as they practice. These laboratory approaches impose barriers to the accessibility of motor learning assessments that could provide valuable information about developmental processes and medical conditions that impact motor control. The development of remote or more portable motor learning measurement tools would greatly expand the ability to assess more diverse populations. To date, there exist a handful of motor learning tools for portable devices like smartphones and tablets but very few completely remote testing options have been developed.

Motor learning follows the law of practice wherein rapid improvements in performance occur initially, followed by more gradual improvements as practice continues. In this sense, we can think of motor skill learning as unfolding in two phases that may rely on different cognitive mechanisms. Recent research has modeled motor learning in an attempt to explain the cognitive mechanisms underlying these performance curve characteristics using a two state, multi-rate model (Smith et al, 2006). Under this theory, motor learning progresses using two processes: a fast process that learns quickly from errors but also forgets quickly, and a slow process that learns slowly, but retains information well. Research focused on identifying the cognitive mechanisms associated with the fast and slow processes have suggested that the fast process is associated with explicit, spatial working memory resources, (e.g., Anguera et al., 2010, 2011; Christou et al., 2016; Keisler & Shadmehr, 2010, Langan & Seidler, 2010; Trewartha et al., 2014; Rajeshkumar & Trewartha, 2019, Wolpe et al., 2020), whereas the slow process is likely driven more by implicit memory or procedural learning (Bond & Taylor, 2015; Shadmehr et al., 2010; Wolpert et al., 2011).

Evidence has shown that motor learning changes with healthy aging and it is thought that the fast process is generally more affected by aging than the slow process (Anguera et al, 2011; Buch et al, 2003; Ehsani et al, 2015; Heuer & Hegele, 2008; Wolpe et al, 2020). This is likely due to larger age-related impairments in explicit learning but smaller changes in implicit learning (Trewartha et al, 2014). This results in older adults being slower to learn novel motor tasks while still eventually learning to the same degree as young adults.

One of the gold-standard approaches to studying motor learning is called the visuomotor rotation (VMR) paradigm (Figure 1). In this task, participants move a cursor representing the position of their hand to visual targets while vision of their hand/arm is occluded (Krakauer, 2009). During the initial phase of the task, participants are simply instructed to guide the cursor to the targets. During the adaptation phase, however, the mapping between hand movements and the movement of the cursor is rotated by some factor (e.g., 45°) in a clockwise or counterclockwise direction from a straight line connecting a start position and the target. Participants must learn to aim their reaching movements by the same factor, but in the opposite direction to guide the cursor successfully to the target. Although the rotation initially disrupts the aiming movements to the targets, people gradually adapt by counteracting the rotation by aiming their hand in the opposite direction (see Shadmehr et al, 2010 for review). Because of this, the VMR paradigm can be used to understand the process by which we adapt and plan new reaching movements (Krakauer, 2009).

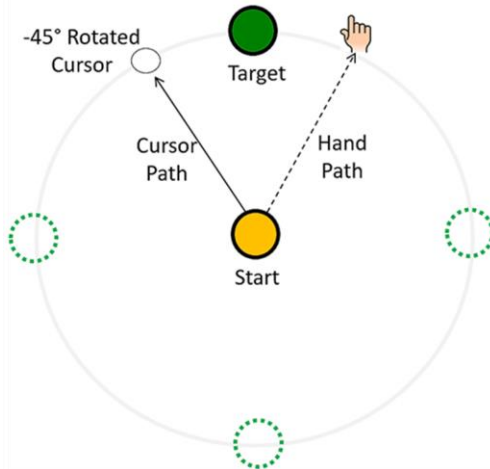


Figure 1. Schematic of the visuomotor rotation (VMR) task. Participants make a reaching movement to guide a cursor from a center start position to a target at either 0, 90, 180, or 270 degrees. During the adaptation phase, the cursor moves 45 degrees away from the path of the participant's hand.

Motor learning tasks like the VMR paradigm are typically implemented using sophisticated equipment and motion tracking equipment. For example, our lab uses a robotic device called a Kinarm (B-kin Technologies, Kingston, ON Canada) wherein participants grasp a handle of a bimanual robotic manipulandum to control a cursor on a horizontal screen. Visual targets are displayed on the display located just above the handles, matching the plane in which arm reaching movements are made. Participants control a cursor on the screen to make reaching movements to the target locations. The screen blocks the participants' view of their hands, the robotic arm, and the handle.

As our understanding of motor learning evolves, we need to focus on more accessible options for testing. Because the Kinarm and many other laboratory-based testing set-ups are not portable, one way of tackling accessibility to develop motor learning tasks for smart devices. Takiyama and Shinya (2016) created the Portable Motor Learning Laboratory (PoMLAB) for just this reason. PoMLAB is an application designed to be used on smartphone or tablet that runs a visuomotor rotation task. Instead of making traditional reaching movements to control the cursor, the cursor is controlled by tilting the tablet or smartphone, engaging the device's accelerometer. The authors noted by doing this, the participants were not given the visual feedback of how their finger moved on the touchscreen in relation to the cursor (Takiyama & Shinya, 2016). PoMLAB has been further used to investigate visuomotor adaptation in inpatient Parkinson's patients in Japan (Takiyama et al, 2020).

Bedore et al (2018) have also created a tablet-based application to investigate visuomotor functioning designed to be used in individuals suspected of having or recovering from concussion or traumatic brain injury either within a sporting arena or rehabilitation facility. The three tasks in their battery (double-step task, interception task, and stop-signal task) were designed to be completed on an Apple iPad with task input coming from the touch screen (Bedore et al, 2018).

While tablet and smartphone apps expand our ability to measure motor learning outside the lab, they still require the researchers to travel to participants or participants to travel to the researchers. Geographical, financial, and temporal constraints thereby still limit the accessibility of these approaches. An alternative way of making such research tools more accessible is to move them to a web-based platform. This allows testing to occur remotely improving the reach to multiple populations of interest. In response to the lack of remote testing options which were made apparent by the COVID-19 pandemic, we created a web-based application to assess visuomotor adaptation in a remote environment. One lab has recently published on their progress in this area. Tsay et al. (2020; 2021) designed OnPoint, an open-source web-based software, to study motor learning in a remote environment. They tested their application by running a VMR task on over 250 participants recruited through Amazon Mechanical Turk and found their results to be comparable to those found in the lab. Similar to OnPoint, our application requires no downloads on the part of the participant. The only requirement is for them to have a computer (laptop or desktop) and an internet connection. This makes the application far more accessible than current laboratory and recently developed portable platforms.

To date, no web-based motor learning platform has been tested with populations other than healthy younger adults. To realize the full potential of this remote approach, web-based platforms must be tested with other populations. Here we evaluated the validity of our web-based motor learning application with groups of younger and healthy older adults. Using a fully remote web-based motor learning assessment tool leaves room for error when testing more specialized populations as the participants are not able to ask questions and the researcher is not able to troubleshoot the application if something goes wrong. For this reason, our approach was to observe participants completing the motor learning assessment by having them share their screen in a Zoom call. This was especially important given that the different generations may have varied experience with computer platforms and web applications that could impact their performance. The overarching goal of this project is to validate the web-based application in younger adults and healthy older adults by comparing their performance to data previously collected in the lab on the Kinarm robot. We hypothesized that the learning curves acquired with the web-based VMR application would not differ from those acquired from a previous sample of younger and older adults in the laboratory. In line with previous research, we also hypothesized that younger adults would adapt to the visuomotor rotation faster than older adults. Finally, given previous observations of a relationship between early and late stages of motor learning and working memory and implicit memory, respectively, we evaluated whether similar correlations would be observed with remote testing. To test this, we asked participants to perform an online cognitive battery in addition to the online VMR task. We hypothesized that early adaptation will be associated with spatial working memory while late adaptation will be associated with implicit memory.

2 Methods

2.1 Participants

We recruited 43 participants including 24 healthy younger adults from 18-29 years old ($M = 19.33$ years, $SD = 2.41$, 9 females) and 19 healthy older adults from 61-86 years old ($M = 72.42$ years, $SD = 8.16$, 13 females) for this study. Young adult participants were recruited through Michigan Technological University's (MTU) psychology subject pool system, SONA, and by word of mouth. Older adult participants were recruited through word of mouth, a newspaper ad, and social media. Prior to participation in the study, interested individuals were informed that they must meet the following criteria: a) free from medical conditions that affect movement of the hands or arms (e.g., arthritis, carpal tunnel syndrome, bradykinesia, long-term complications related to previous injury or surgery); b) free from medical conditions that affect cognitive functioning (e.g., previous head injury leading to unconsciousness, history of multiple concussions, seizures, epilepsy); c) ages 18-35 years old or 60-90 years old; d) familiarity with using a computer and the internet; and e) Access to a desktop or laptop computer and the internet. Participants were also asked to fill out a questionnaire through Google Forms that allowed the researchers to confirm that they met the inclusion criteria.

Comparison data from the laboratory setting came from a previous study which used the same inclusion criteria for younger and older adults. The data from the lab included 26 healthy younger adults from 18-33 years old ($M = 21.31$ years, $SD = 2.98$, 16 females) and 26 healthy older adults from 63-80 years old ($M = 70.42$ years, $SD = 4.47$, 17 females). T-tests showed there was a significant difference in age between the two younger adult groups ($p = .01$, $d = .75$) and no significant difference in age between the two older adults ($p = .55$, $d = .20$).

2.2 Procedures

Participants were provided with all study information and materials via email and the study took place remotely. Prior to meeting with a researcher, participants were also asked to complete a health and demographics questionnaire via Google forms. While in a secure Zoom meeting, participants completed a web-based motor learning task and a battery of web-based cognitive tasks while sharing their screen allowing for researchers to monitor task performance and provide instructions and feedback as needed. Task presentation was counterbalanced. General information about the participant's computer hardware was also collected. This includes whether they were using a laptop or desktop, their operating system, whether they were using a mouse or trackpad to complete the tasks, and the web browser they were using.

2.3 Behavioral Tasks

2.3.1 Motor Task

While in the Zoom meeting, participants were provided with a link that sends them to the web-based VMR application housed on the MTU website. During the task, participants were asked to use either their mouse or laptop trackpad to move a white dot from a center starting location to a target location at either 0, 90, 180, or 270 degrees and back to the center. Importantly, no representation of the cursor's position is shown to the participant. The first phase of the task includes learning trials where the white dot moves congruently with the participant's movement of the mouse or finger on the trackpad. During the middle phases, however, the white dot moves

at an offset of 45 degrees clockwise from a straight line connecting the start position and the target. The goal of these trials is still to have the white dot reach the target location. In the last phase of the task, the rotation is turned off, and the white dot again moves congruently with the participant's movements. Learning curves will be acquired to determine how quickly participants learn to adapt their movements.

The key dependent measure from the VMR task is the angular error of the initial heading angle of the participant's movement towards the target on each trial. The initial heading angle is identified from the position of the cursor when the participant first reaches a point that is one quarter of the target distance. Angular error is calculated by finding the difference between the initial heading angle and a straight line connecting the start position to the target (Figure 2). For each participant, angular error is calculated for every trial and then the average is calculated over every four trials as each target appears once every four trials. By calculating angular error over 4-trial epochs of the adaptation phase, we produced learning curves that represent the speed at which participants learned to adapt their movements.

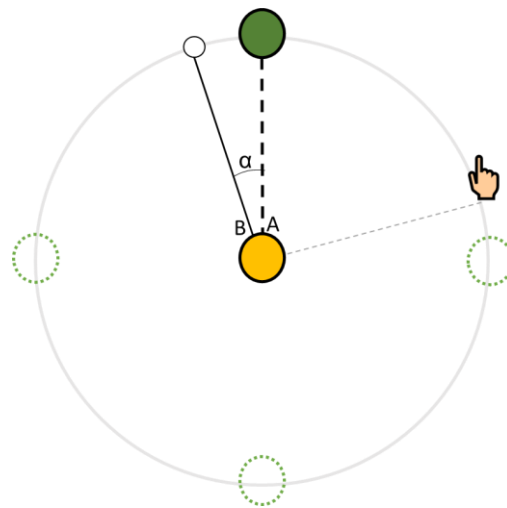


Figure 2. The difference between the initial heading angle of the cursor (Line B) and a straight line to the target (Line A) is defined as angular error (α), the measure of adaptation in the VMR task

The VMR task on the Kinarm is implemented the same way as the web-based version. The number of trials in the practice, adaptation, and washout phases is the same, and the cursor is offset by 45 degrees. Each of the four targets is shown once every four trials, and the target angles are the same as well. The Kinarm differs in that the task is completed using handles connected to a robotic manipulandum that while stimuli are presented on a horizontally oriented screen in the same plane of motion that the movements are made. Participants are also not able to see their hands or arms as they perform the task.

2.3.2 Cognitive Battery

While in the Zoom meeting, participants were also sent a link to an online test battery arranged specifically for this project using the online version of Inquisit (Millisecond Software, LLC, Seattle, WA). Inquisit has both online and local platforms for computer-based psychological

testing to measure a broad range of cognitive constructs. In this study, participants completed three cognitive tasks: a) Corsi Block Task (measuring visuospatial working memory), b) Manikin Test of Spatial Orientation and Transformation (measuring visuospatial mental manipulation), and c) Pursuit Rotor Task (measuring implicit/procedural learning).

In the Corsi Block Task, nine blue blocks were presented on the screen, and they changed to yellow one at a time in a certain order. After watching the sequence in which the blocks change color, the participants were asked to click on the boxes in the same order they were presented to repeat the sequence. The task starts at two-block sequences and can go up to a nine-block sequence. The task ends once a participant completes two sequences of the same number incorrectly. The measure we used from this task was the Block Span measure of spatial working memory, the highest number of blocks in a sequence the participant could complete. In the Manikin Test, participants are shown a drawing of a man inside of a red square or green circle and holding a red square in one hand and a green circle in the other. The man may be facing forwards or backwards and may be right side up or upside down. Participants were asked to indicate in which hand the man was holding the object that matched the background (i.e., if the man was in a red square, they were to indicate which hand was holding the red square). There is a block of practice trials that give the participant feedback about their answers. During the test trials, however, no feedback is given. We used the proportion of correct answers and reaction time for correct answers as measures of mental rotation in this task. In the Pursuit Rotor Task, a blue circle is on screen that acts as a track. During each trial, the participant must try to keep their cursor on a yellow circle that goes around the track. They are given feedback indicating if the cursor is on or off the circle. The difference score between the time spent on the target during the last trial and the first trial was calculated as our measure of procedural memory (learning).

2.4 Data Analysis

All data from the online VMR application were post-processed in MATLAB to extract the heading angle needed to calculate angular error and the 4-trial average epochs. Any trial that had an angular error above or below three standard deviations from the participant's mean angular error was removed. All statistical analyses were completed in R.

To examine our hypothesis that younger adults would adapt to the online visuomotor rotation quicker than older adults, we used a mixed factorial age group (younger vs older adults) by learning phase (epoch of the adaptation phase) ANOVA to compare angular error. Following this initial analysis, we examined the role of input device on the ANOVA results and how movement speed differed between the groups. Next, learning curves acquired from the online VMR application were compared to those acquired from a previous sample of younger and older adults who were tested on the Kinarm. A mixed factorial ANOVA was used to compare angular error with age group (younger vs older adults), epoch, and testing method (application vs Kinarm) as independent variables. Follow-up analyses examining the role of input device were also conducted. Finally, to examine how different cognitive constructs relate to performance on the VMR application, we calculated average angular error across four quarters of the adaptation phase trials and conducted correlation analyses between average angular error per age group in the first (early learning) and fourth (late learning) quarter of the adaptation phase trials with Corsi Block, Manikin Test, and Pursuit Rotor performance.

3 Results

3.1 Participant Flow

Due to technical issues, not all participants completed both the VMR app and the cognitive battery. Twenty-one younger adults and 17 older adults successfully completed the VMR app. This data was used in the analysis of VMR performance. Twenty-four younger adults and 15 older adults successfully completed the cognitive battery. Analysis that compared VMR methods included data from 26 younger adults and 26 older adults that were collected on the Kinarm as part of another study. For analyses that evaluated relationships between cognitive and VMR performance, only participants who successfully completed both VMR and cognitive battery were used: 21 younger adults and 13 older adults.

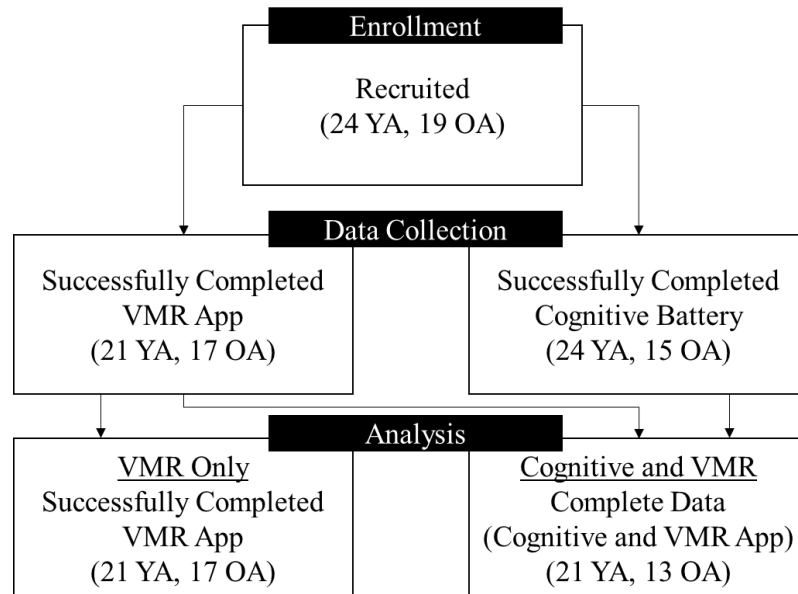


Figure 3. Participant retention throughout the study; data loss was due to technical issues with either the VMR app or cognitive battery. YA = younger adults; OA = older adults.

3.2 Age Differences in Online VMR Performance

3.2.1 Adaptation

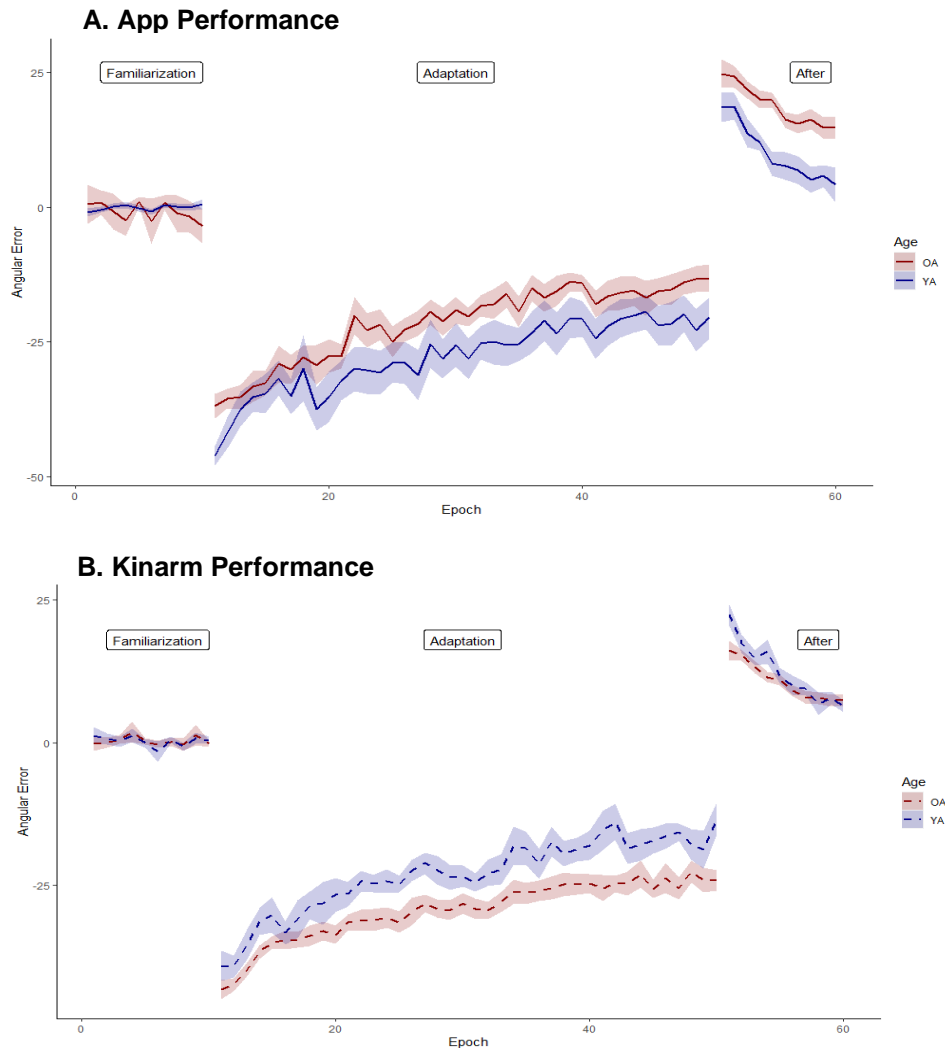
To examine how the age groups differed during the adaptation phase of the VMR app, we conducted an age group by epoch mixed factorial ANOVA. Mauchly's test indicated that the assumption of sphericity had been violated for the main effect of epoch. Therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon=.256$). There was a significant main effect of epoch ($F(9.99,359.80)=21.55, p<.001, \eta_p^2=.374$) which indicates that both groups learned across the adaptation phase. The lack of significant age main effect ($F(1,36)=2.5, p=.123, \eta_p^2=.065$) suggests the visual differences observed in the learning curves (see figure 4a) were not statistically significant, and younger and older adults learned to adapt to the rotation. Also, the lack of a significant age group and epoch interaction ($F(9.99, 359.80)=.616, p=.80, \eta_p^2=.017$) suggests that both age groups learned to adapt to the rotation at the same rate.

3.2.2 After Effects

We also examined how the age groups differed after the rotation was turned off and the cursor was no longer offset. An age group by epoch mixed factorial ANOVA showed a significant main effect of epoch ($F(3.43, 123.32)=19.686, p<.001, \eta_p^2=.354$) and a significant main effect of age ($F(1, 36)=11.5, p=.002, \eta_p^2=.242$). Because Mauchly's test again indicated that the assumption of sphericity had been violated for the main effect of epoch, degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon=.381$).

Figure 4

VMR Performance Between Older and Younger Adults Using the App and in the Lab



Note. Figure 4 presents the learning curves for older and younger adults using the online app (4A) and the Kinarm (4B). Error bars represent standard error. OA = Older Adults; YA = Younger Adults.

3.2.3 The Role of Input Device

We also wanted to examine whether there was an effect of input device (mouse vs. track pad) on angular error data. Because the number of trackpad users (eight younger adults and three older adults) was far less than mouse users, it did not make sense to run an age group by epoch by input device ANOVA. As such, we first examined if there was a significant difference in angular error across the adaptation phase between participants who used a track pad and those who used a mouse. A t-test revealed that those who used a trackpad had an 8.8 degree larger angular error ($p < .001$, $d = .56$) than those who used a mouse.

We were curious if this large difference was responsible for our lack of age group differences seen in our ANOVA. We ran two more age group by epoch ANOVAs for the adaptation and after effects excluding data from participants who used a trackpad. These ANOVA produced similar results, though. For the adaptation phase, there was a significant main effect of epoch ($F(8.12, 203.02) = 75$, $p < .001$, $\eta_p^2 = .365$) but no significant main effect of age group nor a significant age group by epoch interaction. For the after effects, there was also only a significant main effect of epoch ($F(3.22, 119.15) = 11.92$, $p < .001$, $\eta_p^2 = .323$). Again, Mauchly's test indicated that the assumption of sphericity had been violated for the main effect of epoch and Greenhouse-Geisser estimates of sphericity were applied ($\epsilon = .208$ for adaptation and $.357$ for after effects).

3.2.4 Differences in Movement Time

Understanding if there are differences in movement between the two age groups may help us explain the differences seen in angular error. As such, we conducted an age group by epoch mixed factorial ANOVA of the adaptation phase to examine this. Mauchly's test indicated of the assumption of sphericity had been violated for the main effect of epoch. Therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = .198$). The movement time ANOVA resulted in significant main effects of age group ($F(1,36) = 7.28$, $p = .011$, $\eta_p^2 = .168$) and epoch ($F(7.71, 277.61) = 45.6$, $p < .001$, $\eta_p^2 = .559$). A significant interaction between age group and epoch was also found ($F(7.71, 277.61) = 2.31$, $p = .022$, $\eta_p^2 = .060$). Pairwise comparisons showed a much faster average movement time in younger adults ($M = 500.58$, $SE = 23.39$) than older adults ($M = 594.88$, $SE = 25.99$) suggesting that older adults took significantly more time to complete each trial of the adaptation phase than younger adults.

3.3 Effect of Testing Method on Learning Curves

3.3.1 Adaptation Phase

A three-way mixed factorial ANOVA was performed to evaluate the effects of epoch, age group, and testing method on angular error during the adaptation phase. Mauchly's test indicated that the assumption of sphericity had been violated for the main effect of epoch. Therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = .395$). The resulting adjusted ANOVA showed a significant effect of epoch ($F(15.41, 1325.01) = 50.85$, $p < .001$, $\eta_p^2 = .372$). There were no significant main effects of age group or method.

There was a significant interaction effect between age group and method ($F(1,86) = 8.39$, $p = .05$, $\eta_p^2 = .089$). This effect indicates that the angular error as assessed by the different methods (lab vs app) differed between younger and older adults. Specifically, pairwise comparisons showed significant differences in performance by older adults between the lab and app ($p = .008$, $\eta_p^2 = .091$)

and performance by older and younger adults in the lab ($p=.017$, $\eta_p^2=.074$). The age differences in performance seen in the lab were known and consistent with previous literature. Interestingly, there were significant differences between older adults and testing method. Older adults surprisingly performed better on the app (had smaller angular error; $M=-21.05$, $SE=2.46$) than on the Kinarm ($M=-29.40$, $SE=1.81$)

3.3.2 After Effects

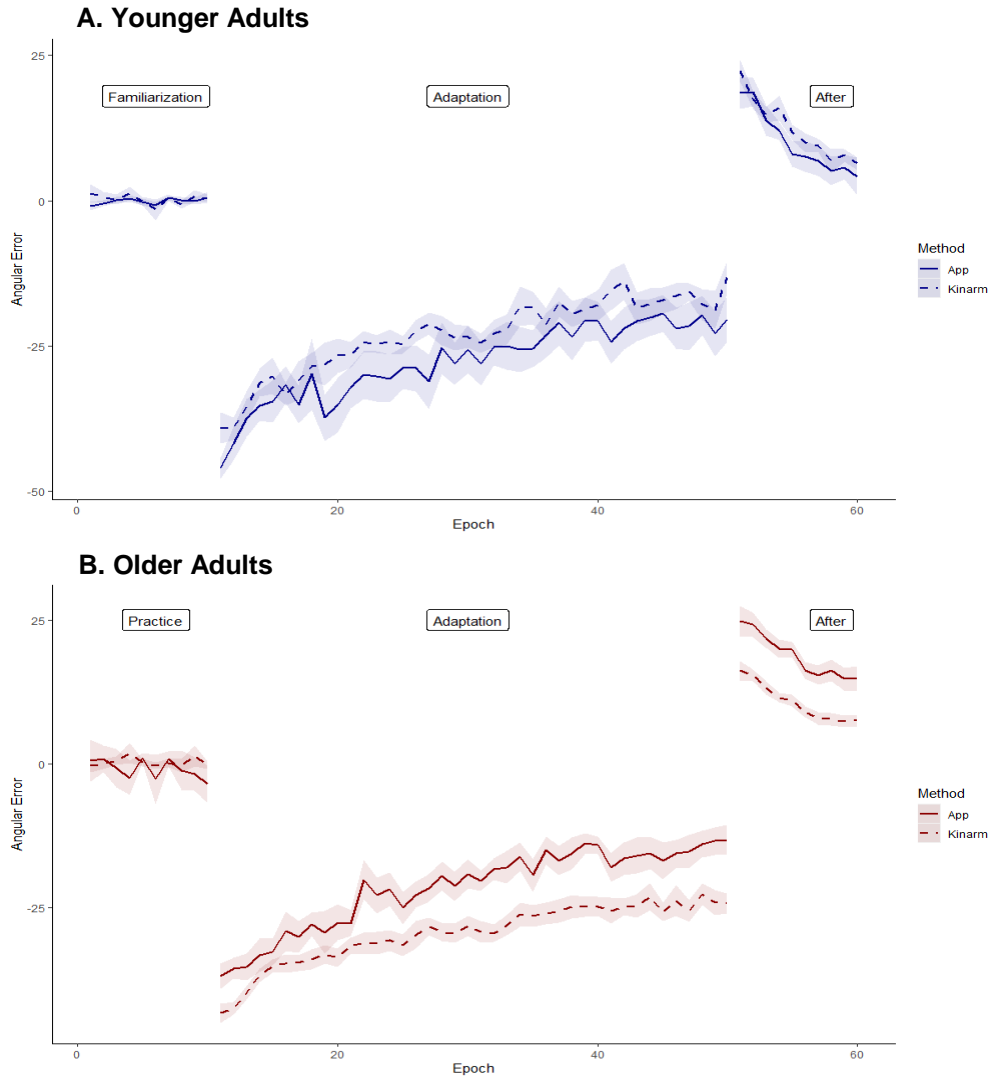
A three-way mixed factorial ANOVA was also performed to evaluate the effects of epoch, age group, and testing method on angular error during the washout phase after the rotation was turned off. Mauchly's test indicated that the assumption of sphericity had been violated for the main effect of epoch. Therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon=.545$). The resulting adjusted ANOVA showed a significant effect of epoch ($F(4.91, 421.88)=56.63$, $p<.001$, $\eta_p^2=.397$), age ($F(1,86)=6.57$, $p=0.012$, $\eta_p^2=.071$), and method ($F(1,86)=4.43$, $p=.038$, $\eta_p^2=0.049$). There were significant interaction effects between age group and method ($F(1,86)=13.65$, $p<.001$, $\eta_p^2=.137$) and age group and epoch ($F(4.91, 421.88)=2.98$, $p=.015$, $\eta_p^2=.033$).

Pairwise tests were performed on both of these interactions. For the age group and method interaction, notably, there were significant differences in angular error between younger and older adults on the app ($p<0.001$, $\eta_p^2=.164$) with younger adults having a significantly smaller angular error ($M=10.07$, $SE=1.42$) compared to older adults ($M=18.79$, $SE=1.58$). There was also a significant difference between older adults on the app and Kinarm ($p<.001$, $\eta_p^2=.156$). Older adults who performed the task on the app had a significantly larger angular error ($M=18.79$, $SE=1.58$) than older adults who performed the task on the Kinarm ($M=10.71$, $SE=10.71$).

3.3.3 Influence of Trackpad

Again, we were interested if the larger angular error produced by trackpad users was responsible for the differences observed between the Kinarm and app users. To test this, we ran the three-way mixed factorial ANOVA (epoch x age group x method) again after filtering out the data from those who used a trackpad ($n=11$) in the app group. Similarly, though, we still saw a significant age x method interaction ($F(1,86)=13.65$, $p<.001$) suggesting that the larger angular error caused by using a trackpad does not account for the differences seen between the Kinarm and app.

Figure 5
Comparisons Between App and Lab Performance for Each Age Group



Note. Figure 5 compares the learning curves between testing methods within each age group. Figure 5A shows the differences in angular error between younger adults who performed the VMR task using the online application and those who completed the task in the lab. Figure 5B shows the differences in angular error between older adults who performed the VMR task using the online application and those who completed the task in the lab. Error bars represent standard error.

3.4 Cognitive Performance and App Performance

To understand how cognitive task performance compared to angular error during the adaptation phase of the VMR app task, we performed correlation analyses. Because the data was not normally distributed for the majority of the variables, non-parametric Spearman’s correlation tests were run.

3.4.1 First Quarter of Adaptation

As mentioned previously, we predicted that early learning (as defined by the first quarter of the adaptation phase) will have the highest correlations with our Corsi Block measure. However, Block Span, our measure from the Corsi Block Task, had a weak, nonsignificant positive correlation with early learning in younger adults and a weak, nonsignificant negative correlation with early learning in older adults. Correlations between angular error and all cognitive task measures can be seen in Table 1.

3.4.2 Fourth Quarter of Adaptation

We also predicted that late learning (as defined by the last quarter of the adaptation phase) will have the highest correlation with the Pursuit Rotor measure. However, Time on Target Difference Score, our measure from the Pursuit Rotor Task, had a weak, nonsignificant negative correlation with late learning in younger adults and a weak, nonsignificant positive correlation with late learning in older adults. Correlations between angular error and all cognitive task measures can be seen in Table 1.

Table 1

Spearman Correlations between Angular Error During Adaptation and Cognitive Task Scores

	Younger Adults			
	Corsi Block: Block Span	Manikin: Proportion Correct	Manikin: Mean RT for Correct Answers	Pursuit Rotor: Difference Score
Angular Error Q1	.20 [-.25, .58]	.18 [-.27, .57]	.27 [-.18, .63]	-.33 [-.66, .12]
Angular Error Q4	.34 [-.10, .68]	.12 [-.33, .53]	.36 [-.09, .68]	-.15 [-.55, .30]
	Older Adults			
Angular Error Q1	-.10 [-.61, .48]	-.39 [-.77, .21]	-.14 [-.64, .45]	.22 [-.38, .69]
Angular Error Q4	-.26 [-.71, .34]	-.17 [-.66, .42]	-.01 [-.56, .55]	.10 [-.48, .62]

Note. Cell entries are Spearman correlations (ρ) between average angular error values for the first quarter of adaptation (Angular Error Q1) and the last quarter of adaptation (Angular Error Q4) and the measures of interest from the cognitive battery. 95% confidence intervals for each correlation are presented in the brackets below the value. No correlations were significant at the $p < .05$ level.

4 Discussion

The overarching goal of this study was to provide evidence that our recently developed web-based VMR application is a valid way to assess motor learning in older and younger adults. The VMR task is a measure of motor learning in which participants must adapt their movements to control a cursor that moves in a direction rotated by 45 degrees relative to their hand movement. This task has been historically administered using specialized equipment in a laboratory setting (e.g., a Kinarm robotic device), making the task less accessible to special populations. Here we evaluated a web-based version of this task to ensure that it provides similar learning assessments compared to a laboratory version in healthy younger and older adults.

Our first key finding is that learning curves produced by participants with the VMR app were similar to those produced on the Kinarm (see figure 4). Our analyses showed that indeed learning did occur, angular error decreased as the task progressed, and both age groups appeared to learn at similar rates. This finding is consistent with other studies that have examined the use of portable motor learning tasks such as PoMLAB (Takiyama & Shinya, 2016; Takiyama et al, 2020) and Bedore et al (2018) iPad-based assessments. Similarly, the other web-based VMR application, OnPoint (Tsay et al, 2020, 2021), showed results comparable to lab studies. Our study went beyond those done by Tsay et al (2020, 2021) and included a healthy older adult sample to test out the app in another population.

We examined whether previously documented age differences in adaptation between younger and older adults were observed using the VMR app. The age comparison using the VMR app data was not significant, contrary to common observations in the literature which show older adults to have reduced adaptation compared to younger adults (Anguera et al, 2011; Buch et al, 2003; Ehsani et al, 2015; Heuer & Hegele, 2008; Wolpe et al, 2020). The reason why this age effect was not observed using our VMR app is not immediately clear, but there are a few possible explanations. First, we suspected that those who used trackpads to complete the app had larger angular errors due to the decreased control of the cursor inherent in using the trackpad compared to a mouse. We found this to be true with almost a ten-degree larger overall angular error in those who used a trackpad as compared to those who used a mouse. As most of the trackpad users were younger adults, we investigated whether the larger than usual angular error in this sample was due to the trackpad users, which could explain our lack of observed age differences. However, after dropping the trackpad users, age differences were still not apparent, and the statistical analyses were similar regardless of whether the trackpad users were included. Second, the lack of age differences in performance using the app could have been related to the fact that older adults had longer movement times than younger adults, potentially allowing for more online corrections and less reliable angular error estimates. These movement time data suggest that the older adults may have used a more cautious response style in their movements than younger adults and this could explain the lack of age differences in angular error.

Our second key finding was that there were differences in performance for both age groups between the app group and the lab group. Notably, younger adults performed similarly when using the Kinarm than the app while older adults performed better using the app than the Kinarm. The trackpad users also did not account for these differences. We suspect that older adults performed better on the app due to their familiarity with a traditional computer set up relative to their unfamiliarity with the Kinarm. There is some evidence in the cognitive aging literature that older adults are more affected by performing tasks in an unfamiliar environment than younger adults. For example, Muffato, Della Giustina, Meneghetti, and De Beni (2015) found that when

asked to point to landmarks in familiar environments, they performed as well as young adults. However, when asked to point to landmarks in unfamiliar environments, they did significantly worse than younger adults. They suggest that this may be due to declines in visuospatial working memory (Muffato et al., 2015). Similarly, being in an unfamiliar environment, especially one with different machinery, can increase environmental monitoring. In turn, this can hinder older adults' ability to process a task properly resulting in disruptions in memory (Stevens et al, 2008). Because the Kinarm is in the lab and operates in a drastically different way than any other device older adults generally use, their performance may be impacted by these differences in environment.

Our third key finding is that our cognitive measures were not associated with learning at any stage of adaptation. Previous literature suggests that early stages of motor learning are likely associated with explicit, spatial working memory (e.g., Anguera et al., 2010, 2011; Christou et al., 2016; Keisler & Shadmehr, 2010, Langan & Seidler, 2010; Trewartha et al., 2014; Rajeshkumar & Trewartha, 2019, Wolpe et al., 2020), while later learning is likely associated more with implicit learning (Bond & Taylor, 2015; Shadmehr et al., 2010; Wolpert et al., 2011). In this study, however, our measure of spatial working memory was not significantly correlated with performance in the first quarter of the adaptation phase of the VMR app. Our measure of procedural learning was also not significantly correlated with performance in the last quarter of the adaptation phase. This was true for both younger and older adults. Interestingly, there were no significant correlations between any of the cognitive measures during the first nor the last quarter of the adaptation phase.

Our study is not without limitations. First, a larger sample size would provide a more robust assessment of the correlational results observed in this study. We ran into many technical issues with older adults running the applications, especially the cognitive tasks. This resulted in fewer data points than we had anticipated. Also, finding older adults willing to perform computerized tasks over Zoom was difficult, and may have resulted in a biased sample. Second, we had a handful of younger adults in our sample who performed surprisingly poorly on the VMR app given their age. This likely dragged down the overall younger adult performance and could be another reason for the lack of age differences seen in the app data. Interestingly, there has been renewed interest in the field in individual differences in learning curves in sensorimotor adaptation tasks (Moore & Cluff, 2021) and it would be informative to examine individual differences in learning using online apps as well.

The main findings of the current study introduce many questions for future research. First, collecting more data from both younger and older adults using the app will allow us to compare the effects of trackpad versus mouse users to determine if there is a true effect of input device. Larger samples will also allow us to examine whether the effect of input device varies by age group. Second, future studies should make additional efforts to better equate the movement times of those using the app to ensure that the angular errors are not biased for any particular group. Here, we provided feedback about their movement speed for each trial, but this was not sufficient in regulating the movement speed across age groups. Third, future analyses could examine differences in “good” and “poor” learners in both age groups to further explain the lack of age differences observed in the current data. Lastly, additional comparisons of performance differences across operating systems, browsers, or other hardware and software configurations should be performed to establish whether these factors impact learning curves in either age group.

In summary, the current study shows that our newly developed VMR web-based app is able to assess motor learning in both younger and older adults in a remote environment. The unexpected results in differences between testing method (app versus Kinarm) and lack of associations with cognitive measures may be due to our small sample size. However, our data show that the VMR app can be used in research with results that are similar to those acquired in a laboratory setting. The benefit of this app is to improve the accessibility of the VMR task to broader populations than are typically recruited for laboratory studies. Future research with this app is aimed at further add validity evidence of its use in other specialized populations such as rural communities, clinical populations (e.g., Parkinson's disease or Alzheimer's disease patients) and increasing usability to ensure it could be used by participants without a researcher present.

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