Differences Between Younger and Older Adults in Whole Body Step Motor Sequence Learning

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Abstract

Motor Sequence Learning (MSL) underlies many of our daily activities. When researched, however, keypress and minor movements are usually examined, which gives insight into underlying processes but can lack the complexity of full-body movements that are crucial to everyday functioning. Few studies have examined this aspect in the older population where physical and cognitive limitations can start to occur which can affect the learning and maintenance of motor sequences. Knowing how older adults differ from young adults in this area can give insight into underlying mechanisms of MSL with regard to ageing that could benefit learning and rehabilitation programs. We piloted the Dance-Step Discrete Sequence Production (DS-DSP) task within the elderly population and examined the differences between motor sequence learning and movement preparation between younger and older adults using both behavioural and kinematical data through motion capture. Five older adults (age = 62.4 ± 3.58, 4 females, 100% right-footed) took part in the study and practised 144 sequences over 6 Blocks. Data from five younger adults from a previous cohort were used for comparison. Results showed that older and younger adults learn differently as their learning slopes differ. Accuracy performance is worse for older adults but reaches a similar accuracy level with practice. No chunking occurred for either group, however, young adults seem to perform the entire sequence as a chunk. For older adults, no chunking occurred although a switch towards the chunking strategy seemed to occur at the 5th Block. Finally, data related to Center of Mass (CoM) acceleration showed that young adults accelerated/decelerated faster than older adults in the block after a break, which may have been due to the exploration of a faster sequence execution that could eliminate the concatenation point they had previously utilized. Further studies should examine this further and adjust study duration for optimal learning.

Keywords: Motor learning, discrete sequence production task, motor chunking, center of mass

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1. Introduction

In whichever way you have come to read this thesis, chances are some form of movement preceded your current endeavor. The movements we make throughout the day take place almost autonomously, without conscious thought necessary to carry out the minute motoric actions needed to function. These actions require motor skills, that we can perform automatically through the retrieval of learned motor sequences. The (re)learning and retaining of these sequences is referred to as Motor Sequence Learning (MSL). With age, this learning process can become more difficult due to physiological changes, cognitive changes, and increased risk of disease such as stroke (Faulkner et al., 2007; Park et al., 2003; Roger et al., 2012). As the ageing population increases (WHO, n.d.), it becomes increasingly necessary to understand how MSL occurs in this group. Many MSL studies have researched young adults, thus being able to compare findings within the elderly population to the younger population can increase our understanding of how underlying mechanisms change and occur with increasing age. This can then be used to facilitate MSL within the growing ageing population and support them in maintaining mobility, health, and an active lifestyle.

A large part of an active lifestyle is staying physically active through endeavours such as walking and full-body movements. Within MSL studies often focus on minor movements such as key presses as these can aid in the understanding of the underlying cognitive and motor function (Rhodes et al., 2004), but these can lack representativeness for larger complex movements. Therefore, a few studies have started to modify these tasks to include the entire body. The Dance-Step Discrete Sequence Production (DS-DSP) task (Chan et al., 2022) is a full-body MSL task utilizing steps in place of key presses and has been previously used to study whole-body MSL in young adults. In the current study, we will pilot the DS-DSP within the elderly population, in which large motoric MSL tasks have seldom been studied even though these abilities are crucial to the continued well-being of this population (Bičíková et al., 2021). The gathered data will be compared to previously studied young adult participants to examine differences in full-body MSL and movement preparation. This will be done through both behavioural measures and motion capture, allowing for additional insight into kinematical differences between young and old in MSL.

1.1 Brief Differences Between Young and Old

Many differences between young and old have already been widely studied. As we age, we are faced with a multitude of cognitive and physiological changes. Neurologically we can see that brain activation typically is less coordinated and integrated in comparison to young adults especially in the prefrontal cortex and basal ganglia (Bishop et al., 2010; Seidler et al., 2010)/ which aid in motor control. Additionally, atrophy of motor cortical regions, corpus callosum, reduced white matter, and decreased dopamine transmission due to ageing can add to motor decline such as the slowing of movement, balance and gait deficits, and coordination deficits (Seidler et al., 2010). Muscular strength also decreases over time (Amarya et al., 2018) alongside increased fatigue and increased force and velocity variability which can impact motor performance. (Hunter et al., 2016). Thus MSL findings from young adults may not be as easily transferrable to older adults, some findings will be discussed below.

1.2 Motor Sequence Learning and the Discrete Sequence Production Task

Motor Sequence Learning has been widely studied and can be defined as the process of learning a motor sequence to eventually perform that sequence nearly effortlessly, quickly, and accurately for the development of skill (Abrahamse et al., 2013). When faced with a new unfamiliar task, performance is typically externally guided and heavily dependent on presented stimuli, but with further practice performance becomes internally guided through a representation of that sequence (Verwey & Abrahamse, 2012).

Studying this learning is often done with short simple tasks such as a keypress task. The Discrete Sequence Production (DSP) is such a task (among others such as the Serial Reaction Time Task (SRT and m x n task) where participants are classically seated in front of a computer screen with four to eight fingers on designated keyboard keys. The display shows corresponding targets, which light up to indicate the need to press the matching key (Abrahamse et al., 2013). A short pause occurs between sequences. One task usually contains two sequences with a sequence length between three and seven and is often practiced for 500 – 1000 repetitions. After practice, a familiar and unfamiliar sequence is performed to serve as a control. The short nature and discreteness of the task allow for more insight into preparation and segmentation mechanisms (Rhodes et al., 2004). De Kleine and Van der Lubbe (2011) used an adjusted go/no-go DSP allowing for further distinction between the preparation and execution phases.

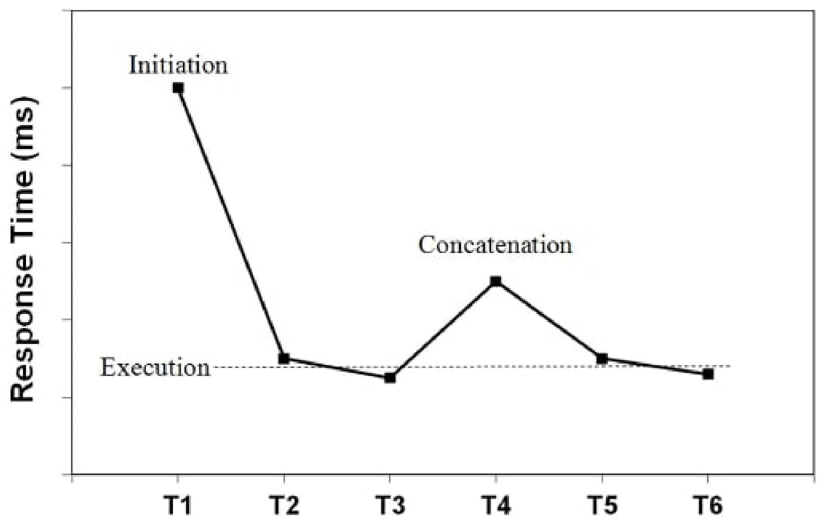
Based on DSP task results and features of several other MSL models the DPM describes the development of discrete sequence skill. It features two processors, a cognitive processor, and a motor processor. These two processors work together in different modes depending on the stage of learning, these being the reactive, associative, and chunking modes (Verwey & Abrahamse, 2012). At the start of learning an unfamiliar sequence, the reactive mode is used in which execution is highly reliant on external stimuli. A stimulus-response (S-R) mapping is made, the cognitive processor selects the correct response based on the presented stimuli and the motor processor executes it. Through practice, the association mode develops. Here external presentation is still required but associations develop between successive sequence elements (and can be on a perceptual, cognitive, or response-based level). Thus, responses are slightly faster as they are primed by the preceding response (Abrahamse et al., 2013). Lastly, the chunking mode can occur, and control starts to occur internally as motor execution is based on motor chunks.

Motor chunks represent several elements of a sequence, that are coded as successive movements (up to 3-4 elements) that can then further be selected and executed as a single response (Verwey & Abrahamse, 2012). The cognitive processor here still selects the correct response, but the motor processor can now execute several elements through the motor chunk, leading to faster execution. It is also thought that the cognitive and motor processors race each other further speeding up execution (Verwey et al., 2010).

The development of this motor chunk can be seen through the RTs, the first response is much slower than the following responses (initiation), the following responses are much faster (execution), and with longer sequences (>4) a relatively slow response shows up halfway through. This slower response is considered the concatenation point, and thought to represent where the transition from one chunk to the next is made (Abrahamse et al., 2013). A typical execution pattern and example of chunking can be seen in Figure 1

Figure 1

Response Time in Sequence Execution



Note. Exemplary RT pattern, showing initiation and concatenation, where concatenation point T4 breaks up the sequence into two 3-sequence chunks. (Abrahamse et al., 2013)

Thus far (and to our knowledge), three MSL paradigms have been created by transferring tasks from keyboard presses to full-body movement tasks. Du and Clark (2018) transformed an SRT task into a foot-stepping task, with the addition of the use of a motion capture system, allowing for the measurement of Centre of Mass (CoM) direction and movement. (Olivier et al., 2021), examined the feasibility of a full body step SRT task and found learning to occur with enough practice in young to middle-aged adults. They later found similar findings in an older adult population (Olivier et al., 2022). In young adults, they found similar patterns in response times as in regular SRTs, but additionally found increased variability in COM movement over blocks which could be indicative of learning. Another paradigm developed by Chan et al. (2022) turns the DSP task into a foot-stepping task coined the Dance Step DSP (DS-DSP), it displays the entire sequence after which participants are asked to perform or inhibit the sequence steps by a go or no-go signal much like De Kleine and Van der Lubbe (2011) key-press DSP task. In the Chan et al. (2022) version young adults showed learning through reduced response time over blocks, showed chunking at the 6th sequence step, and in line with Du and Clark (2018) showed increased CoM velocity variability over block development.

1.3 Expected Motor Learning Differences due to Aging

Within these tasks, older adults are still capable of great learning improvements (Voelcker-Rehage, 2008). There are, however, several findings that older adults seem to learn motor skills differently, with more reliance on external stimuli and different chunking mechanisms (Barnhoorn et al., 2019; Verwey et al., 2010; Verwey et al., 2011).

Differences between older and younger populations have been found in several MSL experiments, most of which look at the neurological and behavioural aspects (RTs, accuracy, retention, etc.). Studies concerning movement preparation and balance within older populations outline more motoric differences and can be combined with kinematical findings from full-body MSL tasks. Findings within these two areas will be described below.

1.3.1 Behavioural differences in motor sequence learning due to ageing

Overall, across tasks older adults appear to perform motor sequences more slowly than younger adults (Barnhoorn et al., 2019; Boyd et al., 2008; Seidler, 2006; Shea et al., 2006; Verwey et al., 2010; Verwey et al., 2011). This could be due to age-related declines in cognitive functioning and information processing, making it harder and more time-consuming for memory retrieval, reasoning, and response selection (Salthouse, 1996; Verhaeghen & Salthouse, 1997). Another factor could be increased biomechanical variability, such as slow fingers (Barnhoorn et al., 2019). Additionally, sequences are performed less accurately, and execution is more variable with age (Panzer et al., 2011;

Vieweg et al., 2023). These performance differences can especially be seen when task complexity increases (Voelcker-Rehage, 2008). Possibly due to factors mentioned above and limited working memory capacity and visuospatial functioning. As a result, elderly may learn differently and utilize different mechanisms and strategies towards MSL than younger adults (Bo et al., 2009; Lingo VanGilder et al., 2020).

Differences can also be found in the utilization of motor chunking. Verwey et al. (2010), found that elderly up to 80 still used motor chunking to a limited degree, often only chunking 3 elements. However, those over 80 showed that they heavily relied on external stimuli and did not make use of the chunking mode, instead using associative learning and having to process and execute their movements one-by-one. This occurs similarly for middle-aged participants, who also rely more on external stimuli, gain less explicit sequence knowledge, and have less developed motor chunks in comparison to young adults (Verwey et al., 2011). Another DSP task showed older adults using chunking similarly to young adults, with older adults requiring more time to develop these chunks (Barnhoorn et al., 2019). These previous results were however also due to slowed effectors at concatenation points, making the use of chunking inconclusive. Bo et al. (2009) similarly showed reduced motor chunk length in an SRT task in older adults and found less older adults to utilize them. Another SRT task showed little use and shorter chunk use by older participants and concurs on less specific sequence knowledge being used by the elderly (Shea et al., 2006). Thus, older adults do seem to form motor chunks to a certain extent but rely on these less efficiently and rely more on external stimuli.

Besides less effective use of motor chunks, slowing could also be due to an execution strategy favouring accuracy over speed. Rabbitt (1979) suggested that older adults may favour accuracy over speed as the speed at which one can respond accurately slows over time. This trade-off favouring accuracy may not be an entirely conscious decision but could be due to changes in brain connectivity (Forstmann et al., 2011). This speed-accuracy trade-off has been seen in linguistic learning and other experiments with elderly (Brébion, 2010; Salthouse, 1979), in motor sequence learning findings are more disjointed, we can see lower accuracy in the elderly with unrelated to speed (Swanson & Lee, 1992), speed reductions and intact accuracy (Bottary et al., 2016), and cases in which lower speed aids accuracy (Vieweg et al., 2023). Overall, however, both speed and accuracy are reduced for the elderly in comparison to young adults.

Another possible mechanism underlying performance change is the shift from explorative strategies towards exploitative ones. Older adults gain a wide range of knowledge throughout life and tend to choose known options whereas young adults prefer exploration and investigating other possibilities (Spreng & Turner, 2021). Lee and Ranganathan (2019) found limited exploration in older adults in an upper-body machine-interfaced motor learning task, leading to worse task performance.

1.3.2 Kinematical differences in motor sequence learning due to ageing

Few studies have examined MSL in the context of a task involving the lower body. Several tasks have involved larger movements than keypresses such as flexor extension, grasping, or object rotation and placement tasks which mostly involve seated participants and upper limb movements. Tasks such as these have shown that age negatively influences anticipatory motor planning, fine motor dexterity, and perceived movement comfort (Stöckel et al., 2017). These tasks also increase the need for sensorimotor processing, which seems largely unaffected in older adults with tasks often showing a similar rate of learning (King et al., 2013; Seidler, 2006). In fact, it seems that the elderly show more task-specific sensorimotor learning, perhaps to compensate for the lack of explicit sequence learning, activation of sensorimotor brain areas has been linked with higher accuracy (Cornelis et al., 2016; Durand-Ruel et al., 2023).

Studies using kinematic analyses have shown that movements produced by older adults typically differ in acceleration and deceleration phases, where the deceleration phase is longer than the acceleration phase, whereas this is usually equal for younger adults. Furthermore, peak velocity is slower and over longer distances older adults don’t increase the velocity of their movements to the extent that younger adults do (Ketcham & Stelmach, 2004). This decreased velocity has also been observed in the COM during stepping and walking tasks (Hurt & Grabiner, 2015; Khanmohammadi et al., 2015). It was further shown that older adults show more variability on movement duration, velocity, and acceleration (Cooke et al., 1989).

There is the added difficulty in a stepping task of postural control. Older adults have shown more difficulty remaining balanced in a single space, showcasing a postural sway when instructed to remain still, especially when eyesight is impaired (Ketcham & Stelmach, 2004). Thus, stepping and balancing these steps adds complexity, and Choice Stepping Reaction Time tasks have been shown to be indicative of fall risk, with slower RTs indicating more risk (Lord & Fitzpatrick, 2001; Pijnappels et al., 2010). Interestingly, Muijres et al. (2023) found that rather than an accuracy-speed trade-off elders might deal more with an accuracy-stability trade-off in stepping tasks, as reduced balance control leads to less accurate stepping. Speed-accuracy trade-offs were similar between young and older adults. Duarte and Freitas (2005) mentioned a similar speed-accuracy-stability trade-off whereas accuracy demands increase, those with high postural variability will be more affected in terms of speed and accuracy as balance needs to be retained.

It is important to note the importance of variability in movement during preparation and execution. (Stergiou et al., 2016) noted the necessity of movement variability in creating a movement plan aiding motor skill performance. This variability decreases with age resulting in more difficulty acquiring motor skills and adapting them.

1.4 Current Study

The current study aims to investigate the differences in motor sequence learning between older and younger adults within the DS-DSP. As a pilot, it concurrently examines the feasibility of such a study and the different behavioural and kinematical facets that can be examined with the DS-DSP.

Based on the previous literature it is expected that:

1. Older adults will show similar learning improvements as younger adults but will overall be slower (Barnhoorn et al., 2019; Boyd et al., 2008; Seidler, 2006; Shea et al., 2006; Verwey et al., 2010; Verwey et al., 2011). This learning progression will be shown through an overall reduction in response times over blocks as shown in the learning curves.

2. Additionally, it is expected that the elderly will have lower accuracy in the DS-DSP, as accuracy is often found to be lower for the elderly (Panzer et al., 2011; Vieweg et al., 2023), possibly due to the additional difficulty in balancing (Duarte & Freitas, 2005; Muijres et al., 2023).

3. Furthermore, smaller, and more limited chunking is expected to occur within the DS-DSP for the older adults in comparison to the young adults. This would be in line with the findings of other MSL studies comparing young and older adults (Barnhoorn et al., 2019; Bo et al., 2009; Verwey et al., 2011).

4. Lastly, less variability in COM acceleration is expected to occur between older adults in comparison to younger adults during movement preparation over blocks. More variability over blocks is indicative of learning and of a movement plan during preparation (Chan et al., 2022; Stergiou et al., 2016), which is expected to occur for both to a certain extent, but we expect it to occur faster and more for young adults. More variability could also result from more explorative behaviour which the elderly tend to use less (Lee & Ranganathan, 2019). Alternatively, the elderly do exhibit more postural sway which could be picked up as CoM variability (Ketcham & Stelmach, 2004). But overall, we expect this variability to occur more for young adults.

2. Methods

2.1 Participants

To examine the differences between younger and older adults, previously collected data was used for the younger adults (Wiechmann, E. (2021)) This was a corpus of data consisting of 24 participants collected in 2021 (18-35 years old), for equivalence 5 participants were randomly selected. Older adults ranging in age from 58 to 67 were recruited through flyers and advertisements online at elderly organizations, physiotherapy practices, and personal circles of the researcher within a 20 km radius of the University of Twente. It was required that participants were healthy, having no history of neurological, psychological, or psychiatric disorders, no addictions to tobacco, alcohol, or drugs, no signs of cognitive impairment, and no obvious physical injuries. Additionally, participants should not have received professional training for dancing, playing a musical instrument, typing, or gaming. For the older participants, it was required to have had no falling incidents in the previous year and to be active for at least 30 minutes a day to ensure their ability to participate and increase the likelihood of experiment completion. To motivate participation, it was advertised that completing the experiment would give a chance of winning a 20-euro supermarket voucher, of which 3 would be distributed.

Five older adults (age = 62.4 ± 3.58, 4 females, 100% right-footed) took part in the study. The project was approved by the ethics committee of the University of Twente, Faculty of Behavioural, Management, and Social Sciences under number 230190. All participants provided informed consent. Five younger adults took part in the previously conducted study (age = 22 ± 1.87, 3 females, 60% right-footed).

2.2 Material and apparatuses

2.2.1 E-Prime®, Dance Mat, JoyToKey (Behavioural)

For stimulus presentation and behavioural data collection, E-Prime® was used. E-Prime® was used due to its ease of use in terms of programming, high control of experiment features such as timing of presentations, and time-accurate recording of responses (RT and accuracy). The original script (unadjusted to the current study) was programmed in E-Prime version 2.0.10.356 (available on The Open Science Framework: https://osf.io/zmxay/download and Github https://github.com/Eggcite/DS_DSP). The script ran on a laptop which was connected to a wide screen television for presentation of the stimuli. The screen was a 77-inch, HDR LG model nr. OLED77CX6LA, with 3840 x 2160-pixel resolution and 120 Hz screen refresh rate. It was positioned approximately 2.0 m away from the participant at a viewing angle of around 120°. A commercially available dance mat was used for the participants to step on (Nonslip Dance Pad Version 5, Figure 2a). The dance mat has 6 areas that can serve as input, for the DS-DSP task the arrow

Figure 2

Dance Mat and Set-Up

(a) *Dance Mat* (b) *Participant Set-up*

areas (↑, ↓, → , ←) were used during task execution and the X symbol was used to initiate the task. The middle non-reactive square served as the neutral position. To convert the steps to usable input JoyToKey ((https://joytokey.net/en/) was used. In JoyToKey ↑, ↓, →, and ← were mapped to keyboard keys W,S,D and A respectively. X and O were mapped to space and enter. 3 chairs were positioned in front, and to the sides of the dance mat at a comfortable arm's length, to serve as a safety measure for them to hold on to when they needed to as can be seen in Figure 2b.

2.2.2 Motion Capture: Xsens MTW Awinda and Analyze (Kinematic)

Figure 3

Sensor Placement

Note. Circles highlight sensor placements (adapted from Xsens (n.d.-b). Lower leg sensors were placed on the outer sides of the lower leg and the pelvis sensor (not visible) was placed on the backside.

Motion capture technology was used to measure several center of mass (CoM) variables (velocity, acceleration, and position) (Xsens, n.d.-a). The Xsens MTw Awinda system uses up to 20 sensors from which precise location information is extracted through complex algorithms (Paulich et al., 2018). The current study focused on CoM movement, for which a lower body configuration of seven sensors is minimally required. The lower body configuration requires the sensors to be placed around the pelvis, left and right upper leg, left and right lower leg, and left and right feet as shown in Figure 3. The sensors transmit data wirelessly through Wi-Fi to the MTw Awinda base station and recorded at an update rate of 100 Hz. The MTw base station was connected to a separate computer which ran the accompanying software MVN Analyze allowing for recording, processing, and extraction of the kinematical data.

2.2.3 Configuration of Behavioural and Kinematical Components Together

The systems interact through the local ethernet. Events or moments of interest within the task are connected to event markers in E-Prime, these markers are sent through to the MVN software via the local ethernet utilizing the User Datagram Protocol (UDP), allowing for fast and time-sensitive transmission. The recording of these incoming markers in MVN allow us to couple the kinematic data to the time points at which the task and steps are occurring. For an overview of all components see Chan (n.d.).

2.2.4 Questionnaires

Three questionnaires were used to assess demographic data, fatigue, and mental workload. The first questionnaire examined demographics and footedness for the purpose of the study and asked for weight, length, and height to use as inputs for the MVN Analyze software. This first questionnaire was only taken at the onset of the study. The other two questionnaires were administered at the onset to get a baseline, and were further administered halfway through after block 3, before the test phase after block 6, and at the end after block 8. The fatigue questionnaire included 7 questions on a Likert scale from 1 to 5 asking about physical and mental fatigue in general, due to the task, and due to attention retainment, and whether fatigue led to drowsiness or a loss of concentration. The NASA-TLX short version was administered as well to examine workload. All questionnaires were translated into Dutch by the researcher for comprehensibility amongst the participants and can be found in Appendix A.

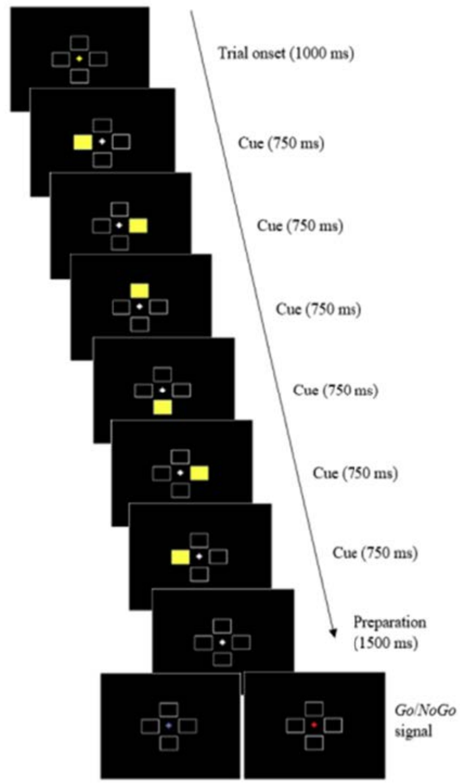
2.3 Task

In the current task the participants practiced two 6-element sequences, which were counterbalanced across participants to account for foot-specific responses. A single trial consisted of the six sequence steps which were presented through four rectangles with a cross in the middle on a black background. At trial onset these white outlined rectangles and yellow cross would be presented for 1000 ms. Then the sequence would be displayed by which the target square would fill with yellow for 750 ms and then the next target until the entire sequence was displayed. This is followed by a preparation state in which the participants see a white cross with the empty squares for 1500ms, which is then followed by either a Go or NoGo stimuli, for which the cross in the middle would turn blue or red respectively as shown in Figure 4. After a Go stimulus participants were tasked with reproducing the sequence they had seen on the corresponding areas on the dance mat, while a NoGo required them to wait as the program continued to the next sequence after 3 seconds.

Go's and NoGo's made up 92% and 8% of the trials respectively. After participants completed a sequence, 'good!' was displayed on the screen in case of correct sequence execution. If mistakes were made feedback was given by presenting which steps were executed incorrectly one by one.

Figure 4

Example of a Trial from Onset, Sequence, to Go/NoGo signal



In total, the experiment had 8 blocks, in which the first 6 blocks comprised the training of the sequences and the last 2 blocks the testing. In the testing blocks participants would get the familiar trained sequences in one block, and unfamiliar rotated sequences in another block, with order of familiar and unfamiliar being counterbalanced across participants. Each block consisted of 24 performed sequences, with 12 of each sequence being performed in random order. Within the block, a 30 second break is presented halfway through to prevent fatigue, and a 3-minute break was held after each block, except for block 4 after which a 10-minute break was held. In the previous DS-DSP study each block contained 48 sequences, but due to concerns of safety, fatigue, and ability to complete the experiment blocks were halved into 24 sequences.

2.4 Procedure

Prior to the experiment, older participants were screened in a phone interview to examine their ability to participate and to check whether they fit the study population.

When this was the case, an appointment was made and participants were informed via email of the appointment, study purpose, and what they could expect, and received a reminder 24 hours before the experiment to not drink or take medication that could affect their balance.

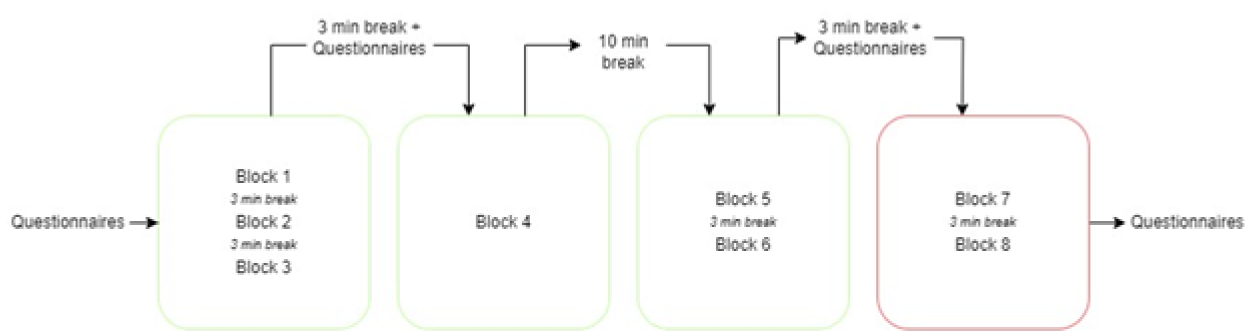
On the day of the experiment, participants were welcomed to the lab, since student assistants were present it was explained that their purpose was to assist and learn more about research. Participant were given the informed consent form (Appendix B) outlining the study's purpose and their right to leave. Once they provided written consent, the participants would get three questionnaires, one only used at the start to determine footedness and record height, weight, and foot length to be put into the MVN Analyze software to determine CoM movement. These were measured by the researcher for accuracy. The participants then had to fill in a fatigue questionnaire and the short form of the NASA-TLX. Then the Xsens sensors were placed around the participants' pelvis, thighs, lower legs, and feet, being mindful of the participants' comfort and ensuring consent before touching them. Once on, the participants were informed of the need to calibrate the sensors for proper recording accuracy. This involved comfortably standing in place, walking for 3 seconds, turning, and returning to the original stance. Turning points were indicated on the floor with duct tape and the MVN Analyze software provided audio instructions which were supported by the researcher. Once calibration was good, the task was explained.

For the task participants were instructed to look at the stimulus presentation screen, remember the sequence, and depending on the blue or red cross go perform the previously viewed sequence on the mat as seen, or not perform the sequence at all. They were informed that the chairs surrounding the mat were there for their safety and they were free to use these for support and that their starting position should be on the centre of the mat. They were further instructed to avoid stepping on one arrow with two feet at once to avoid accidental double keypresses, apart from that they were free to decide upon their movement strategy as they saw fit. If there were no further questions, the recording in the MVN Analyze would start and the E-Prime script would run. Throughout the task, the participant had to be centred back to the origin in the software, as over time sensor drift can occur. At the end of the task, a 3-minute break was held, and a backup of the Motion Capture recording was done. This continued for all 8 blocks with a longer 10-minute break in the middle and the measures of NASA-TLX and fatigue being taken after certain points. The entire outline of this can be found in Figure 5.

Overall, preparation took around 30 minutes depending on how well the calibration was, and the rest of the task took around 1.5 – 2.5 hours with much variability depending on how quickly the participants performed the sequences.

Figure 5

Outline of Experiment Process



Note. The first questionnaire round included a demographic questionnaire the rest included the NASA-TLX and Fatigue questionnaire as outlined in 2.2.4 Questionnaires. The green blocks signify training blocks and the red block signifies test blocks

2.5 Data Preprocessing

Behavioural data from E-Prime was read and processed using Python 3.8, scripts can be found in Appendix D an C. The data reading script extracted the data from the text files that were created out of the ePrime data files, and the arranging script combined all participant files into one and sorted them by subject and retained the relevant data. As sequences performed in training were not equivalent for the younger and older participants, only the first three trials of the younger adults were used. These blocks were split into halves to gain the equivalent number of blocks and trials performed. These adjustments were made manually within Excel. No raw data were excluded. Kinematical data was converted to Excel tables and further processed in R, due to recording issues participant 2 has missing data in the first part of the 2nd training block, recording continued regularly after the 30-second break. This led to missing data for 12 trials. Kinematical data was restricted to the pre-motor phase in which the last 1000 ms before execution were partitioned into sections of 100 ms, giving 10-time points. The R script for kinematical data processing can be found in Appendix G.

2.6 Data Analysis

For Data Analysis RStudio version 4.2.2 was used. Raw data was first examined to visually determine learning. To examine accuracy a linear mixed effect model was used with Block and Group as fixed effects and Subject as a random effect. For the Trial level model a linear mixed effects model was used and the effect of Trial and Block was examined on Response Time with Trial and Block as fixed effects and Subject as a random effect. For the Step level model another linear mixed effects model was used with the effects of Group by Session by Step on Response Times with Subject as a random effect. To examine the kinematical data a linear mixed effect regression model was used looking at the effect of time, block, and group upon the centre of mass acceleration. This was done three times to account for the acceleration on the x, y, and z orientations. Post hoc tests were ran accordingly.

3. Results

3.1 Descriptive Statistics

In Table 1 we see the overall means for both groups, overall the older adults seem to have been slower than the younger adults and seem to also have more variable response times.

Table 1

Mean Overall Response Time and Standard Deviation Across Groups

Group	Overall Mean RT(SD)
Old	837.80 (483.41)
Young	633.40 (275.98)

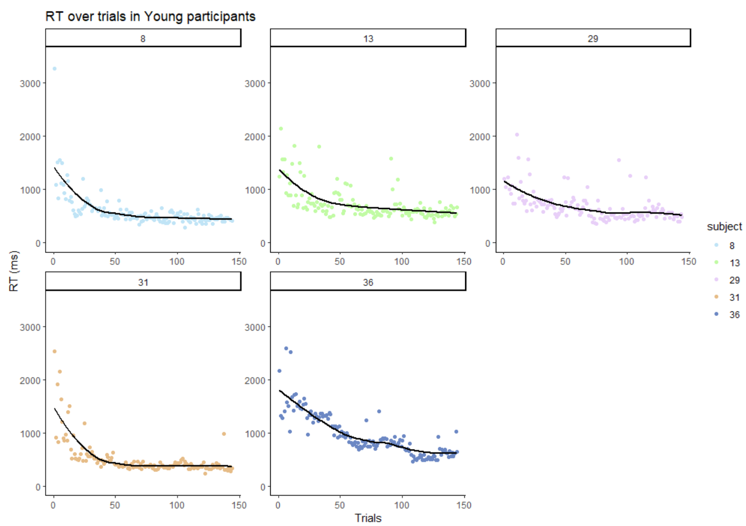
3.2 Raw Behavioural Data

To examine the learning of participants, raw data was first visualized. In Figure 6 we can see the trial means over all trials per participant. We see that the young adult reaction times seem to follow similar curves apart from Participant 36. For older adults learning seems to be more variable with differing curves and a bigger spread of reaction times with the exception of Participant 5.

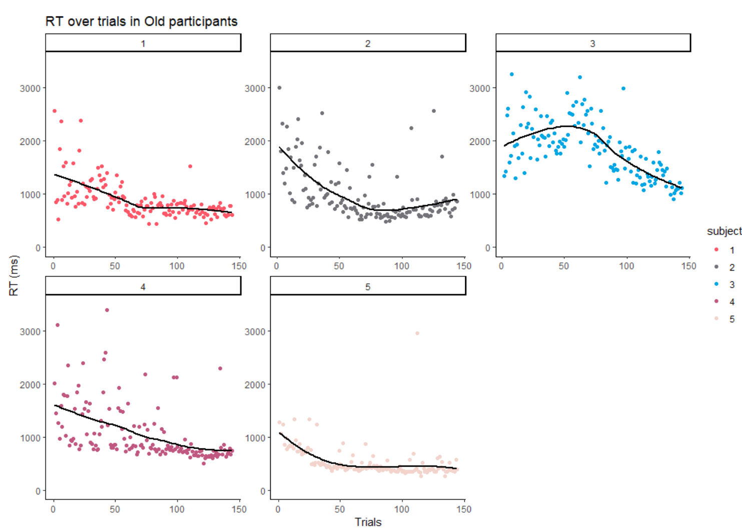
Figure 6

Raw Data Visualization of Learning Curves Over Trials

(a)



(b)

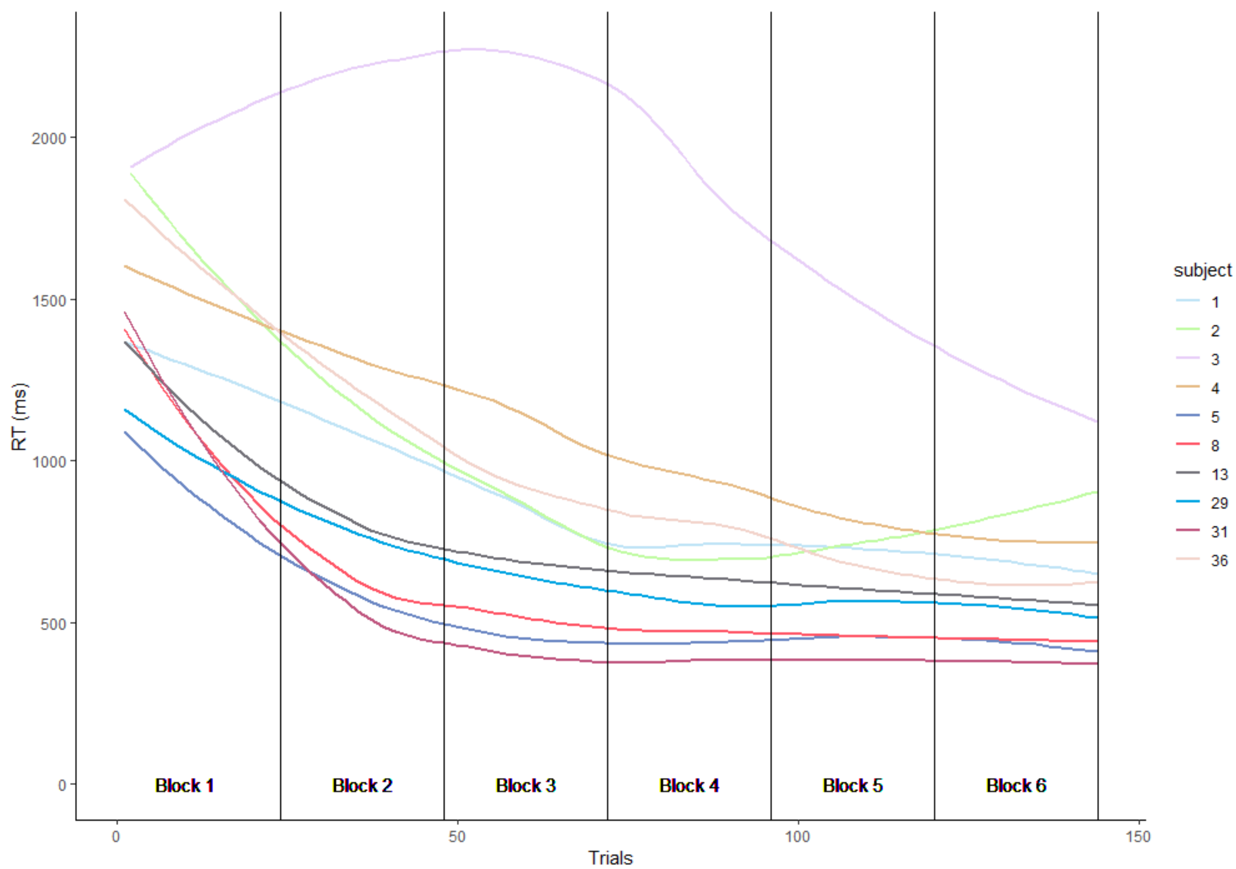


Note. Raw data visualized per participant with Young Adults (a) and Old Adults (b). Outlier trials 2.5 standard deviations above the mean were excluded. We can see a general decrease in reaction times per participant indicating learning.

In Figure 7 all the participants are combined, and progress can be seen over the six training blocks. Once again, we can see that participants in the elder group have more deviation within their learning, most participants show learning across blocks as RTs decrease over time.

Figure 7

Individual Raw Learning Curves Combined



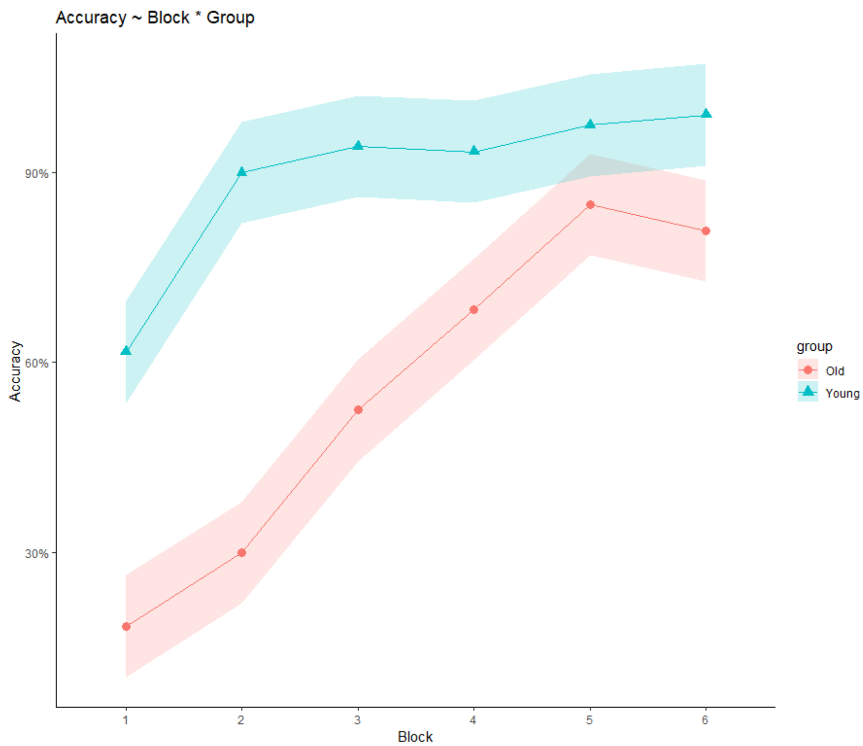
Note. Raw data visualized across participants (OA = subject 1-5, YA = subject 8-36) across blocks and trials. Each curve demonstrates RTs in ms over the 6 training blocks.

3.3 Accuracy

In Figure 8 below, we see the development of the percentage of accurate trials over blocks per group. To examine this relationship a linear mixed effects model was used with subjects as a random effect to account for individual differences. This revealed a significant effect of Block on Accuracy $\chi^2(1, N = 10) = 388.39$, $p < .001$, of Group on Accuracy $\chi^2(1, N = 10) = 21.65$, $p < .001$, and of Block*Group on Accuracy $\chi^2(1, N = 10) = 80.51$, $p < .001$. As can be seen, the older adults started off with lower accuracy which gradually reached the young adult level of accuracy, and the younger adults started off with higher accuracy which gradually improved.

Figure 8

Accuracy Percentage over Blocks by Group



Note. Linear-mixed effect model of accuracy across blocks by group with subject as a random effect. Accuracy is seen to increase for both groups with a steeper increase for the older group in which accuracy percentages are lower at the starting blocks.

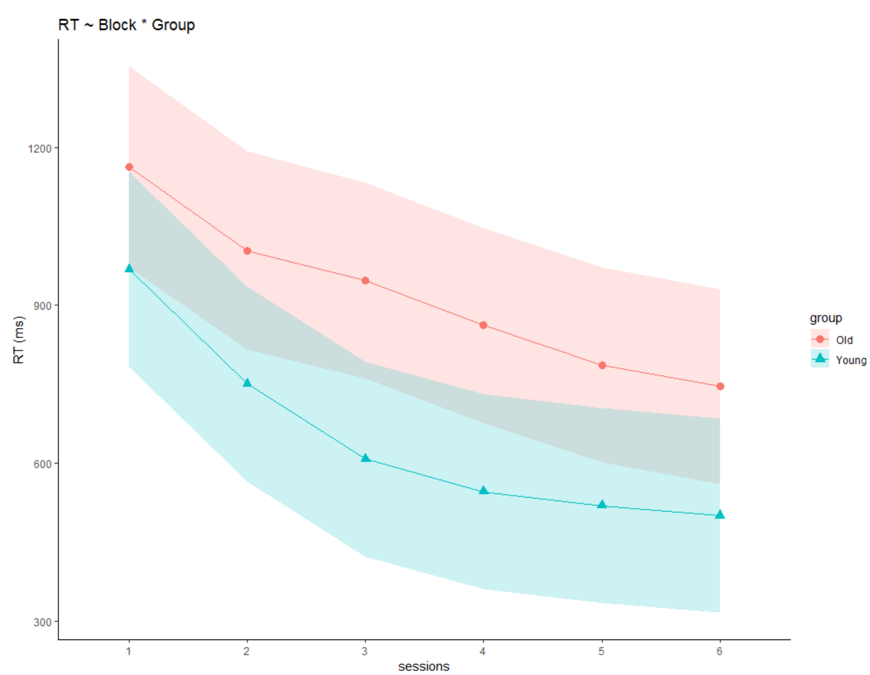
Post-hoc Tukey tests with Kenward-Roger degrees of freedom on Accuracy and Block, and Block*Group showed that accuracy was significantly lower for older adults from block 1 to 4 (Block 2 ($p < .0001$), Block 1 and 3($p = .0001$, Block 4 ($p = .01$). Block 5 and 6 did not significantly differ in accuracy between groups (Block 5 ($p = .18$), Block 6 ($p = .054$). Within the older adult group Block 1 was significantly lower in accuracy for all ensuing Blocks ($p < .0001$) apart from Block 2 which did not significantly differ ($p = .09$). Blocks 2 and 3 had significantly lower accuracy than all following Blocks ($p < .0001$, apart from Block 3 in comparison to Block 4, $p = .006$). Block 4 was significantly less accurate than Block 5 ($p = .003$), but did not differ from Block 6 ($p = .06$). Nor did Block 5 differ in accuracy from Block 6 ($p = 0.94$). For the young adults only Block 1 was significantly lower in accuracy in comparison to all following blocks ($p < .0001$). All other blocks did not significantly differ from each other in accuracy ($p > .3$)

3.4 Trial Level Model

To examine the effect of group and block upon RT a linear mixed effects model was used where subjects were considered a random effect to account for individual learning differences. This revealed a significant effect of Block on trial RT $\chi^2(5, \text{N} = 10) = 668.7$, p

Figure 9

Response Time over Blocks by Group



Note. Linear-mixed effect model of response time (RT) in ms across blocks by group with subject as a random effect. Only accurate trials included 2.5 SD away from the participants block mean. RTs are seen to decrease over blocks with overlap between the confidence intervals between groups.

$< .001$, and a significant interaction of Block*Group on trial RT $\chi^2(5, N = 10) = 14.83$, $p = .01$, Group did not have a significant effect on response time $\chi^2(1, N = 10) = 2.15$, $p = .14$. Figure 9 shows decreasing RTs over the blocks but overlap occurs in the confidence intervals between groups.

The model estimates show the Block*Group effect to occur in the third and fourth sessions in comparison to the first session. Younger adults are significantly faster in the third and fourth session in comparison to older adults in the first session.

Post hoc Tukey tests with Kenward-Roger degrees-of-freedom tests on RT by Group, Session, Session*Group, and Group*Session were carried out. Session contrasts showed decreasing response times overall, with nearly all consecutive blocks being significantly faster than the previous (Block 3 to 4 ($p = .0006$), Block 4 to 5 ($p = .02$), remaining Blocks apart from 5 to 6 ($p < .0001$)). Only the 6th Block was not significantly faster than the 5th Block ($p < .44$), indicative of a plateau. Group contrasts showed no effect of Group upon RTs ($p < .23$). Nor did Group*Session tests show an interaction effect upon RTs ($p < .14$).

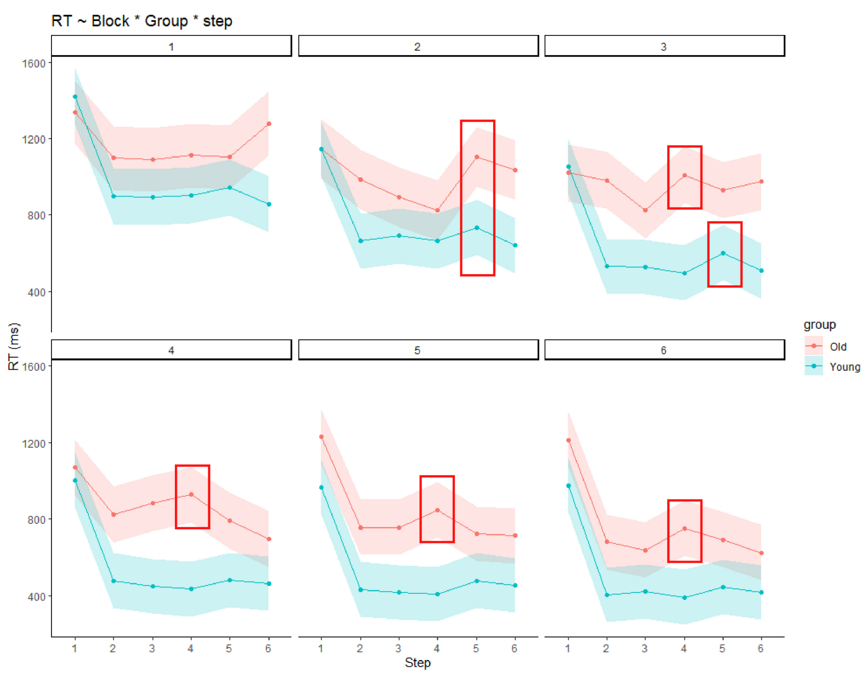
Session*Group contrasts showed that older adults were not significantly faster in the 3rd Block compared to the 2nd Block ($p = .58$), neither did their response times significantly decrease from the 5th to the 6th Block ($p = .52$). Apart from these two occurrences older adults did significantly decrease their response times when Blocks are compared to the following blocks (Block 1 to 2 ($p = .007$), Block 2 to 4 ($p =.0004$), Block 3 to 4 ($p = .032$), Block 4 to 5 ($p = .028$), remaining contrasts ($p < .0001$)). For the younger adults, some of the later Blocks don't show significant decreases in response time. Block 4 is not significantly faster than Block 3 ($p = .058$), Block 4 does not significantly differ in response time from Block 5 ($p = .83$), and Block 6 ($p = .30$), and responses in Block 6 are not significantly faster than in Block 5 ($p = .96$). All other blocks show significant decreases in response time when compared to later blocks (Block 3 to 5 ($p = .0008$), all other Block contrasts $p < .0001$).

3.5 Step Level Model

To examine chunking differences between the old and young group another linear mixed effects model was run based on the effect of step by group by block on the RT, with subjects once again considered as a random effect. The model revealed significant effects for Session $\chi^2(5, \text{N} = 10) = 566.97$, $p < .0001$, Step $\chi^2(5, \text{N} = 10) = 940.32$, $p < .001$, Group*Block $\chi^2(5, \text{N} = 10) = 13.73$, $p = .017$, Group*Step $\chi^2(5, \text{N} = 10) = 55.66$, $p < .0001$, and Group*Session*Step $\chi^2(25, \text{N} = 10) = 55.25$, $p = .0005$ on response time. In Figure 10 it is seen that elder groups RTs stay higher across the blocks, and there is an upwards trend in RT at the fourth step in blocks 3, 4, 5, and 6.

Figure 10

RTs per Step over Blocks by Group



Note. Linear-mixed effect model of RT per step across blocks by group with subject as a random effect. Boxed in red are possible concatenation points. Only accurate trials included 2.5 SD away from the participants block mean.. Note the continued concatenation point at the fourth step in the older adults and the flattening of that point in the younger adults

Post hoc Tukey tests with asymptotic degrees of freedom tests were run. These showed no interaction of Group*Session on RT ($p > .08$), Group*Step on RT ($p > .1$). Tests on Group*Session*Step showed several significant differences. In session 3 at step 2 younger participants were 449.8 ms faster than older adults ($p = .03$), in the same session at step 4 young participants were significantly faster by 513 ms ($p < .02$), and at the 6th step 423 ms faster ($p < .03$). Similarly in session 4 at step 3 young adults were 435 ms faster than older adults ($p < .03$), and at step 4 494 ms faster ($p < .02$). In session 5 this continues with younger adults being 440 ms faster at the 4th step ($p < .03$). Showing significant differences between the groups' response times per step in certain sessions.

Within the Step*Group*Session contrasts differences in RTs of steps within groups and sessions are found. For the 1st session, the older adults showed no significant differences in RTs between steps ($p > .4$), with young adults clear initiation was seen with the first step being significantly slower than all the other steps ($p < .0001$). In the 2nd block older adults only differ significantly between the 1st and 4th step ($p < .03$), young adults still show the slow initiation step ($p < .0001$). In block 3 older adults show no significant RT differences between steps ($p < .03$), and younger adults still had a slower first step ($p < .0001$) with no further differences. In the 4th block older adults show a significant difference between step 1 and step 2, 5, and 6 ($p < .01$) indicative of initiation. Younger adults still showed initialization ($p < .0001$). In the 5th block older adults show a significantly slower first step in comparison to the other steps ($p < .0001$), this is similar for the young adults ($p < .0001$). In the 6th block the same holds, no other significant differences between steps are found within either group besides the first step.

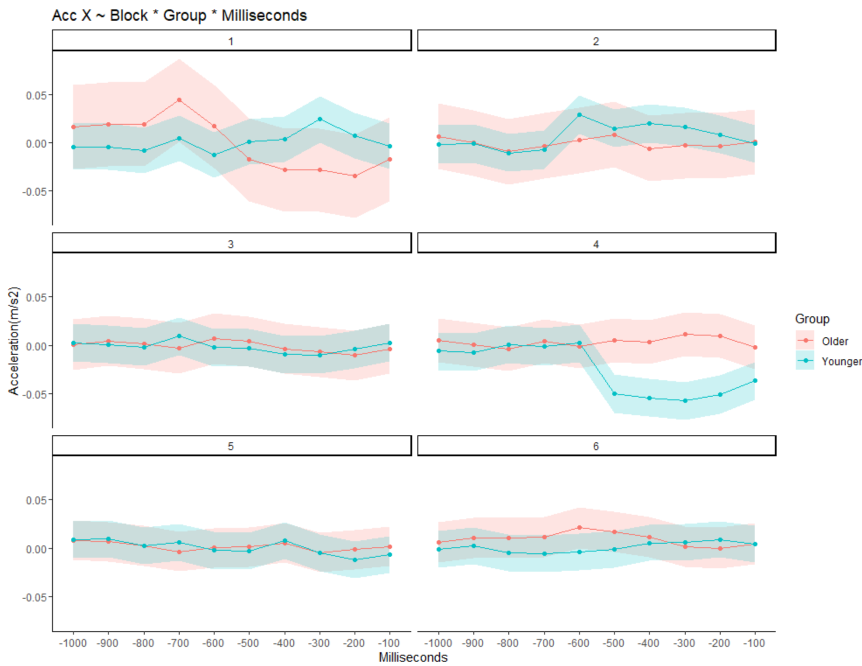
3.6 Kinematic Analyses

3.6.1 X-axis Acceleration

For acceleration on the X axis, Block showed a significant effect $\chi^2(5, N = 10) = 21.54$, $p < 0.001$, as did the interaction of Block*Group $\chi^2(5, N = 10) = 15.81$, $p < .01$. Post hoc tests with asymptotic degrees of freedom showed significant differences in Block 4 between the groups as can be seen in Figure 11 below. In the 4th Block young adults negatively accelerate ($p < .001$) keep to a stable acceleration.

Figure 11

X-Axis Acceleration in Pre-Motor Phase over Blocks by Group



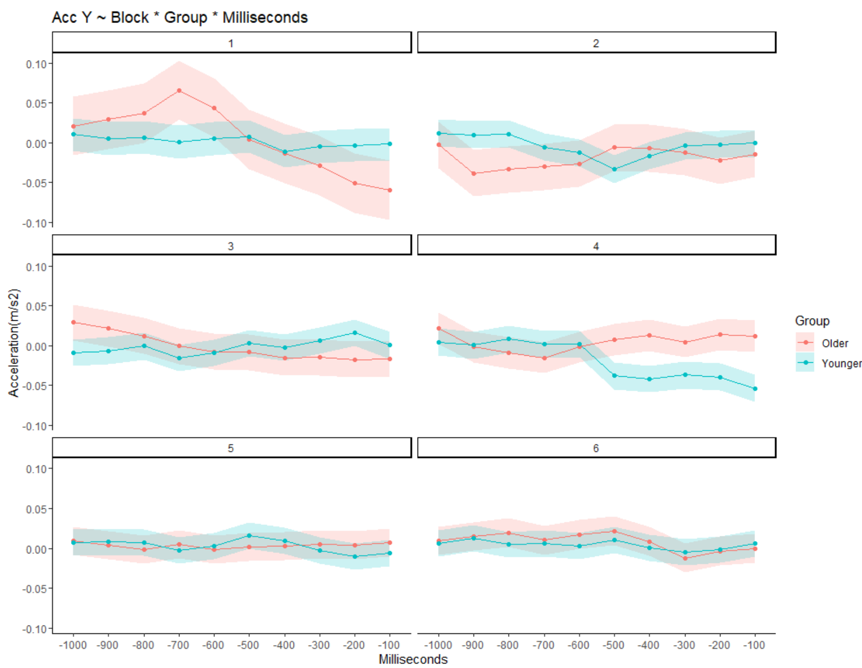
Note. Only accurate trials included

3.6.2 Y-Axis Acceleration

For acceleration on the Y axis, Block showed a significant effect $\chi^2(5, N = 10) = 21.43$, $p < 0.001$, as did the interaction of Block*Group $\chi^2(5, N = 10) = 18.39$, $p < .01$. Post hoc tests with asymptotic degrees of freedom showed significant differences in Block 4 between the groups ($p < .001$) as can be seen in Figure 12 below.

Figure 12

Y-Axis Acceleration in Pre-Motor Phase over Blocks by Group



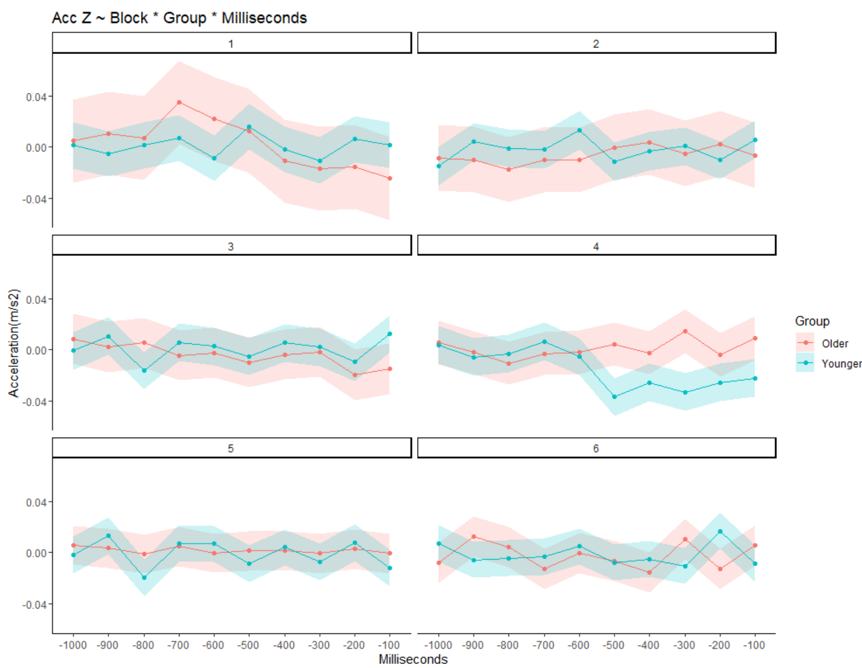
Note. Only accurate trials included

3.6.3 Z-Axis Acceleration

For acceleration on the Z-axis, no significant effects were found. Post hoc tests with asymptotic degrees of freedom were still run an showed significant differences in Block 4 between the groups ($p < .01$) as can be seen in Figure 13 below.

Figure 13

Z-Axis Acceleration in Pre-Motor Phase over Blocks by Group



Note. Only accurate trials included

4. Discussion

The current study piloted the DS-DSP task within the elderly population and examined behavioural and kinematical aspects of MSL during a DS-DSP in older adults. The results imply that there are differences between young and old adults in a full-body MSL task

For the first hypothesis, the trial level model showed a significant interaction effect of Block and Group on Response Times indicating that learning may occur differently for the younger and older adult group over the blocks, post hocs did not show this effect, in Figure 9, we can however visually see a slight difference in slope, Session also had an effect, showing that learning occurred overall. Furthermore, from the raw visualizations, we can see that response times reduced over time indicating learning. Thus the first hypothesis that older adults will show similar learning improvements as young adults but will be slower overall can not be accepted. While response times, in the end, were not significantly different per group there is a different slope as signified by the Block*Group effect indicating different learning over the blocks. Furthermore, older adults are not slower overall as no significant difference was found of group on response time. Post hocs showed that older adults significantly decreased their response times for most consecutive blocks. The reason response times may be similar between the groups could be due to the young adults reaching the asymptote of their learning curve. Post hocs showed that the last blocks did not significantly decrease for them, whereas this was not the case for older adults. So older adults may have a more linear learning curve where it takes longer to reach their asymptote. When looking at the raw data in Figure 6, we can also see older adults having less homogenous curves in comparison to the young adults standard logarithmic curve. Big variation between the older adults could also be the cause of a more linear curve and motoric performance variability is often also higher within older adults (Hunter et al., 2016). Thus, elderly may learn sequences differently and are not significantly slower overall.

This does not fall in line with findings of elderly being slower overall (Barnhoorn et al., 2019; Boyd et al., 2008; Seidler, 2006; Shea et al., 2006; Verwey et al., 2010; Verwey et al., 2011). It can also be seen that the older group combined is slower than the younger group over the blocks as the overall means also reflected (OA(M=837.80 (483.41)), YA(M=633.40 (275.98))). They are however not significantly slower and are also more variable in their response times. The population could play a role in this, as the elderly participants, in this case, were on the younger side (age = 62.4 ± 3.58), whereas Verwey (2010), Boyd et al. (2008), and Barnhoorn et al. (2019) recruited elderly above the age of 70 and 80, where age-related declines may influence motor performance more strongly. Thus, indicating that perhaps, findings of one subgroup within the elderly category may not be transferrable to another. However, the current elderly group was small making these results less conclusive.

The second hypothesis regarding accuracy can be accepted. Older adults were less accurate overall as seen in the significant effect of Group. Accuracy slopes were again significantly different with a similar result in the post hocs as for the trial-level model. Whereas older adults kept significantly increasing their accuracy from one block to another (for most blocks), young adults had this with their first block and afterwards only improved insignificantly. It seems that young adults reach an accuracy plateau that takes longer for older adults to reach. The speed-accuracy trade-off could be a reason why elderly participants performed worse (Rabbitt, 1979), this is however theorized to usually be directed the opposite way where the elderly prefer accuracy at the cost of speed and findings are divided (Bottary et al., 2016; Swanson & Lee, 1992; Vieweg et al., 2023). Muijres et al. (2023) suggested an accuracy-stability-speed trade-off, which could be more applicable in the DS-DSP due to the stepping and requirements of postural balance. Balance could play an additional role as older adults are navigating this new task that requires both balancing, motor planning, coordination control and accurate execution of the step. But this is hard to conclude without more evidence and a measure for balance.

Significant interaction effects were found for Group*Step and Group*Session*Step on RT in the Step level model indicating significant differences in how steps were performed by the groups along the blocks. Post hoc tests could however not find significant differences between steps in blocks by group for chunking, they did show the initiation phase to be different. For the younger adults this makes sense, as the sequence seems to be performed as a single chunk with a slightly longer RT in block 2 and 3 for the 5th step as can be seen in Figure 10. For the older adults it seems that they have a concatenation point on the 4th step in Block 2 - 6. Surrounding execution steps are not significantly different however, suggesting that no chunking is occurring. This means the third hypothesis that older adults would experience more limited chunking is rejected as no chunking seems to occur. It is possible that the training inhibited older adults to chunk properly. Barnhoorn et al. (2019) found breaks to negatively affect their chunking measure in older adults but not younger, having many regular breaks could therefore have inhibited the development of chunking in older adults, especially in comparison to the younger adult group as they had fewer breaks due to the original 48 trials within a block which was adjusted to prevent fatigue. Interestingly, it also takes up to block 4 for the initiation phase to show in the older adult group. This is suggested to be due to the selection and preparation of steps and loading of upcoming responses into a short-term motor buffer(Verwey & Abrahamse, 2012). Following the DPM this is possibly the result of switching from the associative mode to the chunking mode (Abrahamse et al., 2013). While no significant contrasts could prove chunking occurred for older adults, it does seem that they were starting to change towards a chunking strategy, which could be promising for further full-body MSL research with adjusted practice and rest.

For acceleration both the X-axis and Y-axis models showed significant effects of Block and Block*Group. In both models, the post hocs showed this difference to be in the 4th Block where negative acceleration seems to occur for the Young Adult group prior to movement execution. Negative acceleration could mean both slowing down in that direction or speeding up in the opposing direction. This could be indicative of trying a new movement strategy or movement preparation. Spreng and Turner (2021) say that young adults prefer to explore and investigate new possibilities. Block 4 seems to be where the young adult group starts to stabilize in their RTs and accuracy, which could drive that exploration to get better. Lee and Ranganathan (2019) found limited exploration in older adults, which seems to be similar here in the Y- and X-axis acceleration, apart from in the first block as can be seen in Figure 11 and 12. Here there is quite a change in acceleration, which might be due to the first steps leading to imbalance and adjustments. For both groups, acceleration in the Y and X-axis is relatively stable apart from those occurrences.

In the Z-axis acceleration, which is directionally upward, no significant effects were found but post hocs revealed significant differences in block 4 where the young adult seems to accelerate a bit more. It seems both groups within the Z-axis move up and down a bit, perhaps to balance or remain active. The fourth hypothesis stated that less variability was expected to occur in older adults in comparison to young adults. Within the 4th block for all axis, young adults are significantly accelerating more with no significant differences between the other blocks proving that less acceleration variability occurred for the older adults. Thus, older adults may experience less acceleration variability during motor sequence learning.

4.1 Limitations and Future Research

The current study had a limited sample size, making the current findings more indicative rather than conclusive. Studies have shown that individual differences can vary quite a bit within motor sequence learning and the elderly, thus having a larger sample size would allow for better generalizability. Furthermore, previous findings from Barnhoorn et al., (2017) found that a slowing in chunking could be due to a slow effector in older adults. In the current study, it is hard to account for a possible ‘slow leg’, as a particular step can be made by either effector depending on participant preference. Using the motion capture to map the stepping areas virtually could allow for markers to be sent when a certain effector is used for that step, which would allow further insight into the movement strategies of both older and younger adults, which could in turn also provide further insights into the exploitation – exploration theory with regards to movement strategies.

Why accuracy is diminished in older adults could be an interesting point for further research. The current study did not examine the relationship between speed and accuracy and can therefore not conclude anything on that explanation. But further analyses could show possible relationships between these variables. Introducing a force plate, or a balancing and non-balancing group aspect could then also further give more insight into the possibilities of a speed-accuracy-balance trade-off.

Response time is a variable both consisting of the reaction time to the stimulus and the movement time needed for the participant to execute that response. Studies investigating foot-stepping tasks have used methods to disentangle those two by for example considering it reaction once the foot hovers 10cm above the intended space. Being able to separate the two would allow for more insight into whether differences occur through movement time as executed by the motor processor or if cognitive processing is causing a slower response time. Alternatively, (Vieweg et al., 2023) used an 'aging suit' allowing young participants to experience the physical declines of age during a motor sequence learning task. Here the young participants in the suit still performed better than the older adults indicating that cognitive processes may be in part responsible for slower reaction times. This was however a simple MSL task, and using such equipment to compare performance with simulated similar motor functions, but differing cognitive processing could gleam more insight into what causes more slowing in more complex full-body motor tasks.

Using data for the younger adults from a different cohort could also result in peripheral differences between instruction and study execution. The previous data was collected during the COVID-19 period which may have affected certain aspects of data collection. I, however, currently have no reason to believe that these minor differences affected the measures of interest.

5. Conclusion

The current study examined motor learning, accuracy, chunking, and acceleration differences between younger and older adults. The DS-DSP proved to be a viable paradigm to examine learning differences between older and younger adults. Learning occurred in both groups over blocks. Differences between younger and older adults were seen in accuracy with older adults performing worse. The groups also differed in chunking mechanisms with young adults performing the entire sequence as a chunk and older adults not chunking, but starting to chunk. The Centre of Mass variability was more variable for young adults than for older adults. Knowing how motor sequence learning differs between young and old gives more insight into ageing mechanisms affecting motor learning and can provide knowledge to use in rehabilitation, relearning, and falling prevention.

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Appendix A

Questionnaires

Foot Height Weight Start of Block: Default Question Block

Q1 Participant ID?

Q2 Hoe lang bent u?

Q3 Hoeveel weegt u?

Q4 Als u een bal zou moeten schoppen, met welk been zou u de bal dan schoppen?

o Linker (1)

o Rechter (2)

Q6 Stel u voor dat u zou vallen, met welk been zou u dan als eerst reageren om uzelf te stabiliseren?

o Linker (1)

o Rechter (2)

Q7 Welke voet is uw dominante voet?

o Linker (1)

o Rechter (2)

Q5 Wat is uw geslacht?

o Man (1)

o Vrouw (2)

o Ander (3)

Q8 Wat is uw hoogst behaalde opleidingsniveau?

o Geen/onvolledige basisonderwijs (1)

o Basisschool (2)

o Middelbare school (3)

o HBO (4)

o WO Bachelor (5)

o WO Master (6)

o Doctoraal (7)

o Andere, namelijk: (8)

Q9 Welke van het volgende beschrijft uw huidige werksituatie het beste?

o Werkeloos (1)

o Part-time werkzaam (2)

o Full-time werkzaam (3)

o Gepensioeneerd (4)

o Andere, namelijk: (5)

End of Block: Default Question Block

Fatigue Assessment

Start of Block: Default Question Block

Q1 ID

Q2 Session

Q3 Hoe zou u uw algehele vermoeidheid nu beoordelen?

Totaal niet Erg hoog

1 5

Verplaats de slider om aan te geven ()

Q4 Wat is uw mate van fysieke vermoeidheid?

Totaal niet Erg hoog

1 5

Verplaats de slider om aan te geven ()

Q5 Wat is uw mate van mentale vermoeidheid?

Totaal niet Erg hoog

1 5

Verplaats de slider om aan te geven ()

Q6 Wat is uw mate van mentale vermoeidheid wegens de huidige taak?

Totaal niet Erg hoog

1 5

Verplaats de slider om aan te geven ()

Q7 Wat is uw mate van mentale vermoeidheid wegens het behouden van aandacht?

Totaal niet Erg hoog

1 5

Verplaats de slider om aan te geven ()

Q8 In hoeverre leid uw vermoeidheid tot slaperigheid?

Totaal niet Erg hoog

1 5

Verplaats de slider om aan te geven ()

Q9 In hoeverre leid uw vermoeidheid tot een vermindering in concentratie?

Totaal niet Erg hoog

1 5

Verplaats de slider om aan te geven ()

End of Block: Default Question Block

NASA-TLX Dutch Version

Start of Block: Default Question Block **Q1 ID**

Q2 Sessie

Q3 Mentale belasting

Heel laag Heel hoog

0 21

Verplaats de slider om aan te geven ()

Q4 Fysieke belasting

Heel laag Heel hoog

1 21

Verplaats de slider om aan te geven ()

Q5 Tijdsdruk

Heel laag Heel hoog

1 21

Verplaats de slider om aan te geven ()

Q6 Prestatie

Heel goed Heel slecht

1 21

Verplaats de slider om aan te geven ()

Q7 Frustratie

Heel laag Heel hoog

1 21

Verplaats de slider om aan te geven ()

End of Block: Default Question Block

Appendix B

Consent Form

INFORMATIEBLAD

Research project title: Dance-Step Motor Sequence Learning in the Elderly Dit project is goedgekeurd door Universiteit Twentes Behavioural, Management and Social Sciences (BMS) ethiek commissie No. 230190

Onderzoeker Contact details:

Dominique Jansen

Dept. of Cognitive Psychology and Ergonomics

Email: d.jansen-3@student.utwente.nl

Telefoon Nr.: +31642000407

Leidinggevende Contact details:

Dr. Russell Chan (Ph.D)

Dept. of Cognitive Psychology and Ergonomics

Email: r.w.chan@utwente.nl

Telefoon Nr.: +31534896867

Uitnodiging tot deelname in dit onderzoek: U bent uitgenodigd om deel te nemen in dit onderzoek, dat motor sequence learning (het leren van een volgorde aan bewegingen) in relatie tot reactietijd en zwaartepunt beweging onderzoekt. Uw deelname is volledig vrijwillig waarbij uw geïnformeerde toestemming (informed consent) vereist is. U kunt zich op elk moment terugtrekken van deelname aan dit onderzoek zonder consequenties voor u.

Doel van het onderzoek: Dit onderzoek is ontworpen om reactietijd en zwaartepunt beweging te bestuderen terwijl iemand een nieuwe motor sequence leert. Voor dit onderzoek komt u voor slechts 1 testsessie naar het lab om uw data tijdens de oefening op te nemen. Dit wordt gedaan op een computer met een stappentaak terwijl uw reactietijd en bewegingen worden opgenomen met behulp van 7 motion capture sensoren die rondom uw benen, voeten, en bekken zijn vastgemaakt. Geschiktheid voor deelname: Om deel te nemen moet u voldoen aan de volgende vereisten:

1. U bent gezond en tussen de 60 en 75 jaar oud.
2. U gebruikt geen dagelijkse medicatie (m.u.v. Bloedverdunners en hormoonmiddelen, mocht u dagelijkse medicatie gebruiken dan is doktersadvies nodig).
3. U bent niet fysiek gewond en bent goed ter been.
4. U heeft geen valincident of hartproblemen gehad binnen het laatste jaar.
5. U heeft geen leerstoornis, diagnose van geestelijke gezondheidsproblemen of neurologische stoornissen (zoals Alzheimer, Parkinson, Multiple sclerose, hersentumor, hersenletsel, epileptische aanvallen of eerdere hersenschudding/coma).
6. U heeft geen eerdere professionele training gehad in dansen, muziekinstrumenten, gamen, of typen.
7. U heeft niet eerder deelgenomen aan een Motor Sequence Learning experiment in het BMS.
8. U kunt aanwezig zijn voor 1 sessie aan datacollectie gedurende maximaal 1,5 uur.
9. U vindt het niet erg om motion capture sensoren aan uw benen, voeten, en bekken vastgebonden te krijgen.
10. U voelt zich niet onwel in het algemeen.

Geïnteresseerde participanten worden door een onderzoeker vooraf nog een keer nagevraagd naar geschiktheid.

Vereisten: Deelname aan dit onderzoek houdt in dat u EENMAAL aanwezig bent bij een laboratoriumsessie voor maximaal 1,5 uur.

Wat is Xsens en hoe wordt deze data opgenomen?

Xsens is een 3D motion capture programma dat traagheidssensoren gebruik op basis van miniatuur MEMS-technologie. De Xsens traagheidssensortechnologie zal gebruikt worden voor oriëntatie-, snelheids- en positioneringsgegevens.

Lab sessie (1,5 uur): Eerst zult u gevraagd worden om demografische informatie zoals opleidingsniveau, burgerlijke staat, werksituatie etc. Hierna, worden uw afmetingen afgenomen en wordt dit het MVN Analyze programma ingevoerd. Daarna, zult u de xsens sensoren om u heen gebonden krijgen. Deze sensoren communiceren draadloos met het programma. Wanneer het programma en u er klaar voor zijn, zult u gevraagd worden om een kalibratie routine uit te voeren. De routine bestaat uit stil staan, in een rechte lijn lopen, omkeren en weer teruglopen. Dit duurt ongeveer 5 minuten. Hierna zult u een stappentaak uitvoeren waarin u een bepaalde volgorde oefent en daarna een test block. Na het test block zult u geholpen worden met het aftrekken van de sensoren. Om de sessie af te sluiten is er een korte nabespreking en wordt u bedankt voor uw deelname.

Risico's: Dit onderzoek brengt geen risico voor uw welzijn met zich mee, afgezien van wat zou worden verwacht van typische dagelijkse activiteiten. U wordt aangemoedigd om de onderzoekers te informeren als een activiteit te inspannend is en u een pauze nodig heeft. Er is een veiligheidsprotocol aanwezig.

Vergoeding : U maakt bij volledige deelname kans op een 20 euro waardebon van de Jumbo. Er zijn 3 waardebonnen die worden uitgeloot onder de deelnemers als waardering voor uw deelname. Rapportage en onderhoud van data en participant informatie: Alles wat persoonlijke informatie bevat (zoals het ondertekend informed consent) blijven vertrouwelijk en er wordt geen informatie vrijgegeven die kan leiden tot identificatie van een persoon, tenzij wettelijk vereist. Alle onderzoeksgegevens in dit onderzoek worden geregistreerd met een uniek nummer, wat betekent dat uw resultaten niet identificeerbaar zijn.

Er zal geen manier zijn om uw data te identificeren in besprekingen van de resultaten. De verzamelde informatie als deel van dit onderzoek zal 10 jaar bewaard worden en wordt opgeslagen in het kantoor van de leidinggevende (University of Twente Drienerlolaan 5, Cubicus (building no. 41), room B327, 7522 NB Enschede The Netherlands) en op beveiligde elektronische opslag binnen het BMS Lab, University of Twente.

De onderzoeker zal er alles aan doen om antwoorden zo snel mogelijk van identificerend materiaal te verwijderen. Evenzo worden de antwoorden van individuen door de onderzoeker vertrouwelijk behandeld en worden deze niet geïdentificeerd in de rapportage van het onderzoek.

Samenvatting van de bevindingen van dit onderzoek: Wanneer dit onderzoek gepubliceerd zal zijn zal de abstract/samenvatting (Engelstalig) beschikbaar gemaakt worden voor alle participanten. Deze zal via email verstuurd worden als een elektronisch document op verzoek van de deelnemer.

Vrijwilligheid: Deelname aan dit onderzoek is geheel vrijwillig. U kunt als deelnemer uw medewerking aan het onderzoek te allen tijde stoppen, of weigeren dat uw gegevens voor het onderzoek mogen worden gebruikt, zonder opgaaf van redenen. Het stopzetten van deelname heeft geen nadelige gevolgen voor u of de eventueel reeds ontvangen vergoeding. Als u tijdens het onderzoek besluit om uw medewerking te staken, zullen de gegevens die u reeds hebt verstrekt tot het moment van intrekking van de toestemming in het onderzoek gebruikt worden. Wilt u stoppen met het onderzoek, of heeft u vragen en/of klachten? Neem dan contact op met de onderzoeksleider. Dit project is goedgekeurd door de University of Twente BMS ethiek commissie. Als u enige ethische zorgen heeft over dit project, of vragen heeft naar uw rechten als een participant neem dan contact op met de Secretaris van deze Commissie, DR. Lyan Kamphuis-Blikman, tel: +3154893399; email: l.j.m.blikman@utwente.nl

Consent Form (geïnformeerde toestemming) voor Dance-Step Motor Sequence Learning in the Elderly

U KRIJGT EEN KOPIE VAN DIT INFORMED CONSENT FORM

Vink de juiste vakjes aan Yes No

Deelname aan het onderzoek

Ik ben voldoende geïnformeerd over het onderzoek door middel van een separaat informatieblad. Ik heb het informatieblad gelezen of voorgelezen gekregen gedateerd [ ] (DD/MM/YYYY), en heb daarna de mogelijkheid gehad vragen te kunnen stellen. Deze vragen zijn voldoende beantwoord.

Ik neem vrijwillig deel aan dit onderzoek. Er is geen expliciete of impliciete dwang voor mij om aan dit onderzoek deel te nemen. Het is mij duidelijk dat ik deelname aan het onder- zoek op elk moment, zonder opgaaf van reden, kan beëindigen. Ik hoef een vraag niet te beantwoorden als ik dat niet wil.

Ik begrijp dat deelname 1 labsessei betreft en dat data opgenomen wordt op de computer met het xsens programma.

Gebruik van informatie Ik begrijp dat gegeven informatie gebruikt zal worden voor publicatie, conferentie presentaties en wetenschappelijke rapporten

Ik begrijp dat verzamelde persoonlijk informatie over mij die mij zou kunnen identificeren [zoals bijv. mijn naam of waar ik woon], de-identificeerbaar wordt gemaakt en niet zal worden gedeeld buiten het onderzoeksteam.

Toekomstig gebruik en gebruik door anderen Ik geef toestemming om de bij mij verzamelde onderzoeksdata te bewaren in het BMS Datavault en te gebruiken voor toekomstig onderzoek en voor onderwijsdoeleinden

Ik geef toestemming on mijn informatie te delen met andere onderzoekers voor toekomstig onderzoek dat vergelijkbaar is tot dit onderzoek of compleet anders. De informatie gedeeld met andere onderzoekers zal geen informatie bevatten dat mij direct kan identificeren. Onderzoekers zullen mij niet contacteren voor extra toestemming om deze informatie te gebruiken.

Ik geef de onderzoekers toestemming om mijn contact informatie te behouden en om mij te contacteren voor toekomstig onderzoek. Handtekeningen

Naam Deelnemer: Handtekening: Datum:

Naam Onderzoeker: Handtekening: Datum:

Contact details voor verdere informatie over het onderzoek: Dominique Jansen, d.jansen-3@student.utwente.nl

Contact details over uw rechten als participant: Voor bezwaren met betrekking tot de opzet en of uitvoering van het onderzoek kunt u zich ook wenden tot de Secretaris van de Ethische Commissie / domein Humanities Social Sciences van de faculteit Behavioural, Management and Social Sciences op de Universiteit Twente via ethicscommittee-hss@utwente.nl. Dit onderzoek wordt uitgevoerd vanuit de Universiteit Twente, faculteit Behavioural, Management and Social Sciences. Indien u specifieke vragen hebt over de omgang met persoonsgegevens kun u deze ook richten aan de Functionaris Gegevensbescherming van de UT door een mail te sturen naar dpo@utwente.nl.

Tot slot heeft u het recht een verzoek tot inzage, wijziging, verwijdering of aanpassing van uw gegevens te doen bij de Onderzoeksleider.

Appendix C

Python Reading

```
import pandas as pd
import os
import re

#Here you choose the folder with the txt.files you want to merge into an exce
directory = os.getcwd()+r'/Analysis Scripts/23_OlderYounger_Data/txtfiles'
print(directory)

def clean_data(original_df):
    # split up all elements in df into [variable, value] and collect data in
    data_list=[]
    for index,row in original_df.iterrows():
        boolean=row.str.contains(":").sum()
        if boolean>0: row = row.str.split(pat=":")
        data_list.append(row.item())
    print("A session has been added with "+str(len(data_list))+
        " elements in the list containing data from ",end="")

    # remove all tabs and whitespaces from the data
    regex = re.compile(r'[\t\s]')
    for e in range(len(data_list)):
        if type(data_list[e])==list:
            data_list[e][0]=regex.sub("",data_list[e][0])
            data_list[e][1]=regex.sub("",data_list[e][1])
        else: data_list[e]=regex.sub("",data_list[e])
```

```
    return data_list


def get_logframe_indices(my_list):
# create a list with the starting and ending indices of each logframe
    indices=[]
    for row in range(len(my_list)):
        if my_list[row] == '***LogFrameStart***' or my_list[row] == '***LogFra
            indices.append(row)
    return indices


def get_data (initial_df):
#the other two functions are called to clean the data first and get the indic
# where each logframe starts and ends
    part_list=clean_data(initial_df)
    indices=get_logframe_indices(part_list)

    function_columns=["subject","session","procedure","sub trial number",
                      "feedback.ACC","feedback.CRESP","feedback.RESP","feedba
                      "h","cue.OnsetTime","cue.OnsetDelay"]
    file_df=pd.DataFrame(columns=function_columns)

    #subject and session is only assigned once per file
    for row in range(len(part_list)):
        if part_list[row][0] == 'Subject':
            subject=int(part_list[row][1]);print("subject " +str(subject)+"."
        elif part_list[row][0] == 'Session':
            session=int(part_list[row][1]);break
```

```
#loop over starting indices of LogFrames
for i in range(0, len(indices), 2):
#only loop over lines within a LogFrame
    for e in range(indices[i]+1,indices[i+1]):
        if part_list[e][0]=='sequentie' or part_list[e][0]=='Experiment':
        #Level 1 and 5 from text file are excluded
        elif part_list[e][0] == 'Procedure':
            flag=True
            procedure=part_list[e][1]
            (feedbackACC,feedbackCRESP,feedbackRESP,
             feedbackRT,h,cueOnsetTime,cueOnsetDelay)= tuple(["X"]*7)
            if part_list[e][1] == 'cueprocedure' or part_list[e][1] == 'r
                count+=1 #count the sub trial number
            else:
                count=0
        elif part_list[e][0] == 'feedback.ACC':
            feedbackACC=float(part_list[e][1])
        elif part_list[e][0] == 'feedback.CRESP':
            feedbackCRESP=part_list[e][1]
        elif part_list[e][0] == 'feedback.RESP':
            feedbackRESP=part_list[e][1]
        elif part_list[e][0] == 'feedback.RT':
            feedbackRT=float(part_list[e][1])
        elif part_list[e][0] == 'h':
            h=int(part_list[e][1])
        elif part_list[e][0] == 'cue.OnsetTime':
```

```
                cueOnsetTime=float(part_list[e][1])
            elif part_list[e][0] == 'cue.OnsetDelay':
                cueOnsetDelay=float(part_list[e][1])
        if flag:
            data_dict={"subject":subject,"session":session,"procedure":proced
                       "sub trial number":count, "feedback.ACC":feedbackACC,"
                       "feed back.RESP":feedbackRESP,"feedback.RT":feedbackRT
                       "cue.Ons etTime":cueOnsetTime,"cue.OnsetDelay":cueOnse
            file_df=file_df.append(data_dict, ignore_index=True)
            #data from each LogFrame will be added as a row to the df of the
    return file_df

final_df=pd.DataFrame()

#loop over all files in directory
for path in os.listdir(directory):
    path_complete = directory + '/' + path
    #Create initial dataframe
    df_base = pd.read_csv(path_complete, encoding='utf-16')
    #final dataframe of one file will be returned by the function get_data().
    temp_df=get_data(df_base)
    #...and will be added to the overall dataframe
    final_df=final_df.append(temp_df)
#Save the file
final_df.to_excel(r"df_YA.xlsx",index= False)
```

Appendix D

Python Arranging

```
import pandas as pd
import os

df = pd.read_excel(os.getcwd()+r'MA␣Thesis\df_YA.xlsx')

#arrange data on trial level: average RT and overall accuracy
block_columns=["subject","session","trial","sub_trial","accuracy","Mean_RT","
df_block=pd.DataFrame(columns=block_columns)
subjects=[]

for index,row in df.iterrows():
    if row["subject"] not in subjects:
        trial=0 #counts sequences over whole experiment
        sub_trial=0 #counts sequences within one session
        subjects.append(row["subject"])
        sessions=[row["session"]]
    if row["procedure"]=="responsprocedure":
        if row["sub␣trial␣number"]==1:
            trial+=1
            RT = float(row["feedback.RT"])
            accuracy = int(row["feedback.ACC"])
            if row["session"] in sessions:
                sub_trial+=1
            else:
                sub_trial=1
```

```
            sessions.append(row["session"])
        elif row["sub␣trial␣number"]==6:
            RT += float(row["feedback.RT"])
            accuracy += int(row["feedback.ACC"])
            Mean_RT = RT / 6
            Sum_RT = RT
            if accuracy==6:accuracy=1
            else: accuracy=0
            data_dict={"subject":row["subject"],
                       "session":row["session" ],
                       "trial":trial,
                       "sub_trial":sub_trial,
                       "accuracy":accuracy,
                       "Mean_RT":Mean_RT,
                       "Sum_RT": RT,
                       "h":row["h"]}
            df_block=df_block.append(data_dict, ignore_index=True)
        else:
            RT += float(row["feedback.RT"])
            accuracy += int(row["feedback.ACC"])

#create counts for how many times one specific sequence was practiced
subjects=[]
list_h=[]
repetitions=[]

for index, row in df_block.iterrows():
```

```
    if row["subject"] not in subjects:
        list_h=[]
        subjects.append(row["subject"])
    if list_h==[]:
        a=row["h"]
        list_h.append(a)
        a_count=0
        repetitions.append(a_count)
    elif row["h"] not in list_h:
        b=row["h"]
        list_h.append(b)
        b_count=0
        repetitions.append(b_count)
    elif row["h"]==a:
        a_count+=1; repetitions.append(a_count)
    else:
        b_count+=1; repetitions.append(b_count)
df_block["repetition"]=repetitions


#create new column to plot learning curves per subject per sequence
subject=[]
combi_count=-1
combi=[]

for i,r in df_block.iterrows():
    if r["subject"]not in subject:
```

```
            subject.append(r["subject"])
            combi_count+=2
        if r["h"]==1:
            combi.append(combi_count)
        else:
            combi.append(combi_count+1)
df_block["subject_h"]=combi

subjects=[]
for i,r in df_block.iterrows():
    if r["subject"]==8: subjects.append(8)
    elif r["subject"]==13: subjects.append(13)
    elif r["subject"]==29: subjects.append(29)
    elif r["subject"]==31: subjects.append(31)
    elif r["subject"]==36: subjects.append(36)
df_block["subject"]=subjects

df_block.to_excel(r"df_triallevelYA.xlsx",index= False)
```

Appendix E

R: Raw Data Visualization

```
#Prep
df_trial = read_excel("/Behavioural/df_triallevelOAYA_1_final.xlsx")

#create subject factor
df_trial$subject = factor(df_trial$subject)

#get overall mean & SD -> to standardize data
overall_mean <- mean(df_trial$Mean_RT)
overall_SD <- sd(df_trial$Mean_RT)
df_trialsd <- df_trial %>% filter(Mean_RT < (overall_mean+2.5*overall_SD))

#color library for visualizations
mycolors=c("#c0e4f6","#c1fba4","#e8cff8","#e6bc87","#6c88c4","#ff5768", "#747
mycolorsYA=c("#c0e4f6","#c1fba4","#e8cff8","#e6bc87","#6c88c4")
mycolorsOA=c("#ff5768", "#74737a", "#00a5e3", "#c05780", "#f2d4cc")
#create two df's for old and young participants
df_trialYA <- df_trialsd %>% subset(group == "Young")
df_trialOA <- df_trialsd %>% subset(group == "Old")
Learning curves per subject, per group
df_trialYA %>%
  ggplot(aes(x = trial,
             y = Mean_RT,
             color = subject)) +
  geom_point() +
  geom_smooth(se = F, colour = "black") +
```

```
  facet_wrap(~subject, scales = "free") +
  ggtitle("RT over trials in Young participants") +
  ylab("RT (ms)") +
  xlab("Trials") +
  ylim(0, 3500) +
  theme_classic() +
  scale_color_manual(values = mycolorsYA)
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
df_trialOA %>%
  ggplot(aes(x = trial,
             y = Mean_RT,
             color = subject)) +
  geom_point() +
  geom_smooth(se = F, colour = "black") +
  facet_wrap(~subject, scales = "free") +
  ggtitle("RT over trials in Old participants") +
  ylab("RT (ms)") +
  xlab("Trials") +
  ylim(0, 3500) +
  theme_classic() +
  scale_color_manual(values = mycolorsOA)
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
 ## Individual curves all combined
df_trialsd %>%
  ggplot(aes(x = trial,
             y = Mean_RT,
             group = subject,
```

```
               color= subject)) +
  geom_smooth(se = F) +
  scale_x_continuous() +
  theme_classic()+
  ylab("RT␣(ms)")+
  xlab("Trials")+
  scale_color_manual(values = mycolors)+
  geom_vline(xintercept = c(24,48,72,96,120,144),colour="black", show.legend=
  geom_text(aes(x=10, label="Block␣1", y=0.1), colour="black") + geom_text(ae
```

Appendix F

R: Behavioural Analyses

```
# import datasets
df_trial = read_excel("/MA␣Thesis/Analysis␣files/Behavioural/df_triallevelOAY
df_press = read_excel("/MA␣Thesis/Analysis␣files/Behavioural/df_keypress_OAYA

#join datasets for a dataframe including keypresses
df_withstep = merge(x = df_trial, y = df_press,
                    by.x = c("subject", "group", "session", "sub_trial"),
                    by.y = c("subject", "group", "session", "sub_trial"))

#and dataframe without keypresses
df = df_trial
# separate training and testing sessions (shouldn't be in this dataset, but j
df_train = df %>% subset(session <7)

#only keep accurate trials
df_trainacc = subset(df_train, accuracy=="1")
df_trainstepacc = subset(df_withstep, accuracy == "1")

#for trial level
#For trainingsessions 1045/1440 = 72.57% accuracy (lose 17.43% of trials)

#for step level
#trainingsessions 7344/8640 = 85% accuracy

## Calculate the mean value of the session-means, first for all trials then f
```

```r
# variables
train_subjects <- vector()
train_sessions <- vector()
train_means <- vector()
train_SD <- vector()

#variables for accurate trials
train_subjectsacc <- vector()
train_sessionsacc <- vector()
train_meansacc <- vector()
train_SDacc <- vector()




# train set (with inaccurate trials)
for (subject in unique(df_train$subject)) {
  for (session in 1:6) {
    current_session_means <-
      df_train$Mean_RT[df_train$subject==subject
                        & df_train$session==session]

    train_subjects <- append(train_subjects, subject)
    train_sessions <- append(train_sessions, session)
    train_means <- append(train_means, mean(current_session_means))
    train_SD <- append(train_SD, sd(current_session_means))
  }
}
```

```
# create new df with the session means
df_means_train <- data.frame(subject=train_subjects,
                             session=train_sessions,
                             session_mean=train_means,
                             session_sd=train_SD)


#train set with accurate trials only
for (subject in unique(df_trainacc$subject)) {
  for (session in 1:6) {
    current_session_means <-
      df_trainacc$Mean_RT[df_trainacc$subject==subject
                          & df_trainacc$session==session]

    train_subjectsacc <- append(train_subjectsacc, subject)
    train_sessionsacc <- append(train_sessionsacc, session)
    train_meansacc <- append(train_meansacc, mean(current_session_means))
    train_SDacc <- append(train_SDacc, sd(current_session_means))
  }
}

df_means_trainacc <- data.frame(subject=train_subjectsacc,
                                session=train_sessionsacc,
                                session_mean=train_meansacc,
                                session_sd=train_SDacc)
```

```
#do the same for step level
trainstep_subjectsacc <- vector()
trainstep_sessionsacc <- vector()
trainstep_meansacc <- vector()
trainstep_SDacc <- vector()

#train set with accurate trials only
for (subject in unique(df_trainstepacc$subject)) {
  for (session in 1:6) {
    current_session_means <-
      df_trainstepacc$Mean_RT[df_trainstepacc$subject==subject
                              & df_trainstepacc$session==session]

    trainstep_subjectsacc <- append(trainstep_subjectsacc, subject)
    trainstep_sessionsacc <- append(trainstep_sessionsacc, session)
    trainstep_meansacc <- append(trainstep_meansacc, mean(current_session_mea
    trainstep_SDacc <- append(trainstep_SDacc, sd(current_session_means))
  }
}

df_means_trainstepacc <- data.frame(subject=trainstep_subjectsacc,
                                    session=trainstep_sessionsacc,
                                    session_mean=trainstep_meansacc,
                                    session_sd=trainstep_SDacc)
# filter accurate trials which are no more than 2.5SDs away from the mean

# train
```

```
df_trainacc2 <- merge(x=df_trainacc, y=df_means_trainacc, by=c("subject", "se

df_train1 <- df_trainacc2 %>% filter(Mean_RT < (session_mean+2.5*session_sd))

#lose 20 trials, go from 1045 obvs -> 1025 obvs. 1.9% loss within accurate tr

#create factors
df_train1$subject = factor(df_train1$subject)
df_train1$group = factor(df_train1$group)
df_train1$session = factor(df_train1$session)

mycolors=c("#c0e4f6","#c1fba4","#e8cff8","#e6bc87","#6c88c4", "#ff5768", "#74
descriptive statistics
tapply(df_trainacc$Mean_RT, df_trainacc$group, summary)
tapply(df_trainacc$Mean_RT, df_trainacc$group, sd)
tapply(df_trainacc$group, df_trainacc$session, summary)
accuracy model
df$session = factor(df$session)
df$subject = factor(df$subject)
m.df<- lmer(as.numeric(accuracy) ~ session * group + (1|subject), data=df, RE
lmtable <- Anova(m.df)
summary(m.df)

lmtable
plot(m.df)
tab_model(m.df)
#post hocs prep accuracy
```

```
emmip(m.df, group ~ session)
lsmeans(m.df, pairwise ~ group|session)
emmeans(m.df, revpairwise ~ session|group)
emmeans(m.df, revpairwise ~ session)
## NOTE: Results may be misleading due to involvement in interactions
ae.m.df <- allEffects(m.df)
ae.m.df.df<- as.data.frame(ae.m.df[[1]])

ae.m.df.df$l83 <- ae.m.df.df$fit - 1.3722 * ae.m.df.df$se
ae.m.df.df$u83 <- ae.m.df.df$fit + 1.3722 * ae.m.df.df$se

plot(ae.m.df)
#plot accuracy model
ae.accuracy<-ggplot(ae.m.df.df, aes(x=session ,y=fit ,group=group))+
  geom_ribbon(aes(ymin=l83, ymax=u83, fill=group), alpha = 0.2) +
  geom_line(aes(color = group)) +
  geom_point(aes(color = group, shape = group), size = 3)+
  scale_y_continuous(labels = scales::percent) +
  ylab("Accuracy")+
  xlab("Block")+
  ggtitle("Accuracy ~ Block * Group")+
  theme_classic()

plot(ae.accuracy)
Models for learning effect
#Learning Models
m.df_train1.1 <- lmer(Mean_RT ~ session * group + (1|subject), data=df_train1
```

```
lmtable <- Anova(m.df_train1.1)
summary(m.df_train1.1)

lmtable
plot(m.df_train1.1)
tab_model(m.df_train1.1)
post-hocs prep
emmip(m.df_train1.1, group ~ session)
lsmeans(m.df_train1.1, pairwise ~ group|session)

ae.m.df_train1.1 <- allEffects(m.df_train1.1)
ae.m.df_train1.1.df <- as.data.frame(ae.m.df_train1.1[[1]])
ae.m.df_train1.1.df$l83 <- ae.m.df_train1.1.df$fit - 1.3722 * ae.m.df_train1.
ae.m.df_train1.1.df$u83 <- ae.m.df_train1.1.df$fit + 1.3722 * ae.m.df_train1.

plot(ae.m.df_train1.1)
Plot models
#Training Model effects
ae.m.df_train1.1 <- allEffects(m.df_train1.1)
ae.m.df.df_train1.1 <- as.data.frame(ae.m.df_train1.1[[1]])
#Training plot
ae.Trainmean<-ggplot(ae.m.df_train1.1.df, aes(x=session,y=fit,group=group))+
  geom_ribbon(aes(ymin=l83, ymax=u83, fill=group), alpha = 0.2) +
  geom_line(aes(color = group)) +
  geom_point(aes(color = group, shape = group), size = 3)+
  ylab("RT (ms)")+
  xlab("sessions")+
```

```
  ggtitle("RT␣~␣Block␣*␣Group")+
  theme_classic()

plot(ae.Trainmean)
emmip(m.df_train1.1, group ~ session)
emmeans(m.df_train1.1, pairwise ~ group | session)
emmeans(m.df_train1.1, pairwise ~ session | group)
emmeans(m.df_train1.1, pairwise ~ session)
emmeans(m.df_train1.1, pairwise ~ group)
step level
#create factors
df_trainstepacc$subject = factor(df_trainstepacc$subject)
df_trainstepacc$group = factor(df_trainstepacc$group)
df_trainstepacc$session = factor(df_trainstepacc$session)
df_trainstepacc$step_number = factor(df_trainstepacc$step_number)


m.df_trainstepacc <- lmer(feedback.RT ~ group * session * step_number + (1|su
Anova(m.df_trainstepacc)
summary(m.df_trainstepacc, ddf="Satterthwaite")
plot(m.df_trainstepacc)
tab_model(m.df_trainstepacc)
plotting
# Concatenation Model effects
ae.m.df_trainstepacc <- allEffects(m.df_trainstepacc)
ae.m.df_trainstepacc <- as.data.frame(ae.m.df_trainstepacc[[1]])
#Test sessions plot
```

```
ae.3factors<-ggplot(ae.m.df_trainstepacc, aes(x=step_number,y=fit,group=group
  geom_ribbon(aes(ymin=fit-se, ymax=fit+se, fill=group), alpha = 0.2) +
  geom_line(aes(color = group))+
  geom_point(aes(color = group))+
  ylab("RT (ms)")+
  xlab("Step")+
  ggtitle("RT ~ Block * Group * step")+
  facet_wrap(~session, ncol = 3)+
  theme_classic()

plot(ae.3factors)
##posthoc prep
emmip(m.df_trainstepacc, group ~ step_number)
emmeans(m.df_trainstepacc, pairwise ~ group|session)
emmeans(m.df_trainstepacc, pairwise ~ group|step_number)
emmeans(m.df_trainstepacc, pairwise ~ session|step_number)
emmeans(m.df_trainstepacc, pairwise ~ group|session|step_number)
emmeans(m.df_trainstepacc, pairwise ~ step_number)
emmeans(m.df_trainstepacc, pairwise ~ step_number|group)
emmeans(m.df_trainstepacc, pairwise ~ session|group)
emmeans(m.df_trainstepacc, pairwise ~ step_number | group | session)
emmeans(m.df_trainstepacc, pairwise ~ session | step_number | group)
```

Appendix G

R: Kinematic Analyses

```
#Mot df
Xsensacc <- read_excel("/MA Thesis/Analysis files/Kinematical/mvnOAYA_final.x
df_trial <- read_excel("/MA Thesis/Analysis files/Behavioural/df_triallevelOAY

#merge datasets to get crossref accuracy score
Xsensaccwithacc = merge(x = Xsensacc, y = df_trial,
                        by.x = c("Participant", "Block", "Trial"),
                        by.y = c("subject", "session", "sub_trial"))

#subset to get an accurate trials only df
Xsensacc = subset(Xsensaccwithacc, accuracy=="1") #(14266-10436)/14266 = %26.
# for testing
Xsensacc$Participant = factor(Xsensacc$Participant)
Xsensacc$Group = factor(Xsensacc$Group)
Xsensacc$Milliseconds = factor(Xsensacc$Milliseconds)
Xsensacc$Block = factor(Xsensacc$Block)

levels (Xsensacc$Participant)
#Xsens models for differences between groups
m.XsensAccX <- lmer(Acceleration_X ~ Block * Milliseconds * Group + (1|Partic
Anova(m.XsensAccX)
anova(m.XsensAccX)
summary(m.XsensAccX)

m.XsensAccY <- lmer(Acceleration_Y ~ Block * Milliseconds * Group + (1|Partic
```

```
Anova(m.XsensAccY)
anova(m.XsensAccY)
summary(m.XsensAccY)



m.XsensAccZ <- lmer(Acceleration_Z ~ Block * Milliseconds * Group + (1|Partic
Anova(m.XsensAccZ)
anova(m.XsensAccZ)
summary(m.XsensAccZ)
#Retain models of signifiance
m.XsensAccX_2way <- lmer(Acceleration_X ~ Block * Group + (1|Participant), da
Anova(m.XsensAccX_2way)
anova(m.XsensAccX_2way)
summary(m.XsensAccX_2way)

m.XsensAccY_2way <- lmer(Acceleration_Y ~ Block * Group + (1|Participant), da
Anova(m.XsensAccY_2way)
anova(m.XsensAccY_2way)
summary(m.XsensAccY_2way)

m.XsensAccZ_2way <- lmer(Acceleration_Z ~ Block * Group + (1|Participant), da
Anova(m.XsensAccZ_2way)
anova(m.XsensAccZ_2way)
summary(m.XsensAccZ_2way)
#Posthocs Prep
#Posthocs
emmip(m.XsensAccX_2way, Group ~ Block)
```

```
emmeans(m.XsensAccX_2way, pairwise ~ Group | Block )
emmip(m.XsensAccY_2way, Group ~ Block)
emmeans(m.XsensAccY_2way, pairwise ~ Group | Block )
emmip(m.XsensAccZ_2way, Group ~ Block)
emmeans(m.XsensAccZ_2way, pairwise ~ Group | Block)

#Effects of the models
##Alpha
#Need Effects lib
ae.m.XsensAccX<-allEffects(m.XsensAccX)
ae.m.XsensAccX.df<-as.data.frame(ae.m.XsensAccX[[1]])

#change conf interval to 83%, match p = .05
ae.m.XsensAccX.df$l83 <- ae.m.XsensAccX.df$fit - 1.3722 * ae.m.XsensAccX.df$s
ae.m.XsensAccX.df$u83 <- ae.m.XsensAccX.df$fit + 1.3722 * ae.m.XsensAccX.df$s

plot(ae.m.XsensAccX.df)
plot(ae.m.XsensAccX)
##Alpha
#Need Effects lib
ae.m.XsensAccY<-allEffects(m.XsensAccY)
ae.m.XsensAccY.df<-as.data.frame(ae.m.XsensAccY[[1]])

#change conf interval to 83%, match p = .05
ae.m.XsensAccY.df$l83 <- ae.m.XsensAccY.df$fit - 1.3722 * ae.m.XsensAccY.df$s
ae.m.XsensAccY.df$u83 <- ae.m.XsensAccY.df$fit + 1.3722 * ae.m.XsensAccY.df$s
```

```
plot(ae.m.XsensAccY.df)
plot(ae.m.XsensAccY)
##Alpha
#Need Effects lib
ae.m.XsensAccZ<-allEffects(m.XsensAccZ)
ae.m.XsensAccZ.df<-as.data.frame(ae.m.XsensAccZ[[1]])

#change conf interval to 83%, match p = .05
ae.m.XsensAccZ.df$l83 <- ae.m.XsensAccZ.df$fit - 1.3722 * ae.m.XsensAccZ.df$s
ae.m.XsensAccZ.df$u83 <- ae.m.XsensAccZ.df$fit + 1.3722 * ae.m.XsensAccZ.df$s

plot(ae.m.XsensAccZ.df)
plot(ae.m.XsensAccZ)
#plot milliseconds x block x group Z
plot.m.XsensAccZ <-ggplot(ae.m.XsensAccZ.df, aes(x=Milliseconds,y=fit,group=G
  geom_ribbon(aes(ymin=l83, ymax=u83, fill=Group), alpha = 0.2) +
  geom_line(aes(color = Group))+
  geom_point(aes(color = Group))+
  ylab("Acceleration(m/s2)")+
  xlab("Milliseconds")+
  ggtitle("Acc Z ~ Block * Group * Milliseconds")+
  facet_wrap(~Block, ncol = 2)+
  theme_classic()

plot(plot.m.XsensAccZ)
plot milli x block x group Y
plot.m.XsensAccY <-ggplot(ae.m.XsensAccY.df, aes(x=Milliseconds,y=fit,group=G
```

```
  geom_ribbon(aes(ymin=l83, ymax=u83, fill=Group), alpha = 0.2) +
  geom_line(aes(color = Group))+
  geom_point(aes(color = Group))+
  ylab("Acceleration(m/s2)")+
  xlab("Milliseconds")+
  ggtitle("Acc Y ~ Block * Group * Milliseconds")+
  facet_wrap(~Block, ncol = 2)+
  theme_classic()

plot(plot.m.XsensAccY)
#plot milliseconds x block x group X
plot.m.XsensAccX <-ggplot(ae.m.XsensAccX.df, aes(x=Milliseconds,y=fit,group=G
  geom_ribbon(aes(ymin=l83, ymax=u83, fill=Group), alpha = 0.2) +
  geom_line(aes(color = Group))+
  geom_point(aes(color = Group))+
  ylab("Acceleration(m/s2)")+
  xlab("Milliseconds")+
  ggtitle("Acc X ~ Block * Group * Milliseconds")+
  facet_wrap(~Block, ncol = 2)+
  theme_classic()
```