Dancing with your Hands and Feet:
Differences in Sequence Representations Between Effectors

E.M.A.J. (Evelyn) Karelse

University of Twente

Faculty of Behavioural, Management, and Social Sciences (BMS)

Department of Learning, Data-Analytics and Technology

Section Cognition, Data and Education (CoDE)

Master of Human Factors Engineering

Master thesis

First supervisor: Dr. R.W. Chan

Second supervisor: Prof. Dr. W.B. Verwey

20-06-2023

Abstract

Motor sequence learning (MSL) has a substantial impact on our day-to-day lives, as this type of learning is at the basis of many skills. A well-established experimental paradigm to research MSL is the Discrete Sequence Production (DSP) task, which investigates explicit MSL with key-press finger movements. From results of the DSP task, the Cognitive framework for Sequential Motor Behaviour (C-SMB) aims to outline the execution and learning of motor skills. An important real-life application of motor skills is the ability to apply learned skills in novel contexts, i.e. with novel effectors. However, in their classic forms, the DSP and C-SMB mostly describe isolated key-press movements, which do not account for the entire spectrum of movements that underlie many motor skills. Larger, whole-body movements are more complex, focus more on motor execution and are another important part of the spectrum of real-life movements. We conducted a Go/No-Go Dance Step Discrete Sequence Production (DS-DSP) task with 6-element sequences using the hands or feet. A total of 40 participants took part in the experiment, of which half learned two sequences with their hands and the other half with their feet, by 144 repetitions per sequence divided over six practice blocks. To investigate transfer, in the testing phase, participants executed the sequences they learned in the practice phase with the novel effector. Participants who learned with their hands learned faster, showed no concatenation, and had more difficulty integrating new sequences with their learning effector. On the contrary, participants who learned with their feet were slower and showed concatenation. Additionally, participants in the hands group did not transfer motor sequence knowledge to the feet, indicating an effector-dependent sequence representation, which is known to be used at a later learning stage. Simultaneously, participants in the feet group succeeded at transferring motor sequence knowledge to the hands, indicating a visuo-spatial sequence representation, which is known to be used at an earlier learning stage. Finally, participants who practiced with the hands effector had more difficulty integrating two new sequences after learning compared to participants who used the foot effector.

Keywords: Motor sequence learning, discrete sequence production task, concatenation, effector-independent sequence representation, visuo-spatial sequence representation

Contents

1. Introduction **4**

1.1. The Discrete Sequence Production task . . . 5

1.2. The Cognitive framework for Sequential Motor Behaviour . . . 6

1.3. Transfer of motor sequence knowledge . . . 8

1.4. Current study . . . 9

2. Methods **10**

2.1. Participants . . . 10

2.2. Apparatus . . . 10

2.3. Design and counterbalancing . . . 11

2.4. Dance-Step Discrete Sequence Production task . . . 11

2.5. Data analysis . . . 13

3. Results **15**

3.1. Practice phase block-level . . . 15

3.2 Practice phase stimulus-level . . . 16

3.3. Testing phase . . . 17

3.4. Transfer of sequence knowledge . . . 18

Discussion **20**

References **21**

Appendix A **25**

Appendix B **26**

Appendix C **27**

Appendix D **31**

Appendix E **34**

Appendix F **37**

1. Introduction

The importance of motor sequence learning (MSL) can be seen throughout our day-to-day lives, by all behaviours that are based on a learned order of movements. Think of lacing your shoes, typing on a keyboard, or riding a bike (Barnhoorn et al., 2016). Research suggests that these behaviours can be flexibly applied throughout the body, for example, writing with your non-dominant hand or using a bike with pedals for hands instead of feet. A key question in Cognitive Psychology is how individuals learn these behaviours, how the brain represents and controls these motor events, and how these learned motor sequences can be flexibly applied throughout the body (Abrahamse et al., 2013; Verwey, 2001; Verwey et al., 2015). One of the main experimental paradigms to study MSL is the Discrete Sequence Production (DSP, Abrahamse et al., 2013) task. This task is designed to investigate MSL in which individuals are aware of their knowledge and its effects, otherwise known as explicit MSL (Barnhoorn et al., 2016; Rauch et al., 1995; Verwey, 2001).

Throughout this study, the main theoretical model is based on results of the DSP task, namely the Cognitive framework for Sequential Motor Behaviour (C-SMB, Verwey et al., 2015). The C-SMB aims to outline the execution of motor sequences as well as to describe information processing across various motor sequence tasks. This framework also supports the ability to flexibly apply motor sequences throughout the body, or transfer of motor sequence knowledge, through associations between perceptual- and central-symbolic representations (Verwey et al., 2015). This study will focus on MSL and transfer of motor sequence knowledge between the hands- and feet effectors[1]. It is important to study transfer with larger effectors and with movements that include greater motor complexity, as they are an integral part of real-life movements (Du and Clark, 2018). By doing so, we aim to provide a deepening in approximation and understanding of whether transfer of motor sequence knowledge is possible between larger effectors.

1.1. The Discrete Sequence Production task

The DSP task uses two sequences of three to seven stimulus which are presented in random order, typically both with a different first stimulus. Participants then recreate these sequences with key-presses, by pressing the spatially compatible key as quickly as possible following the presentation of the stimulus. The reaction times (RT's) that are the response to single stimuli provide sensitive temporal indicators of underlying cognitive- and motor processes (Rhodes et al., 2004). As participants learn to recognize the entire sequence by its first stimulus, over time the DSP task turns from a [number of stimuli]- RT task into a 2-choice RT task after the initiation of the first stimulus.

RT data from previous research with DSP tasks shows that the execution of a learned sequence has three distinct phases. First is the initiation phase, in which the sequence is selected and prepared based on the first stimulus, and usually consists of the execution of the first stimulus in a sequence (T1, Figure 1, Verwey, 2001). Typically, T1 has a slower RT compared to the rest of the steps in the sequence, which is assumed to be because of preparation and loading of the entire sequence as single stimuli into the motor buffer before

[1] Throughout the current study the terms 'hands effector' and 'feet effector' relate to the acting body part, or the body part that is being used to execute a motor activity. Specific to this paper, the 'hands effector' refers to both hands and the 'feet effector' refers to both feet. There will be no differences made between, for example, the right- or left hand effector.

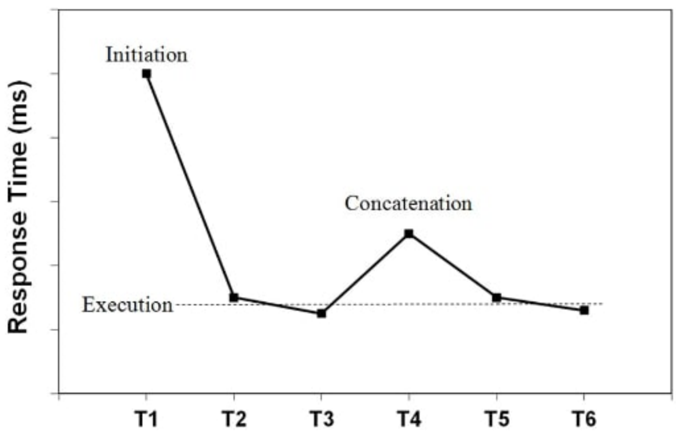

Figure 1

Typical reaction time pattern of the execution of a 6-key sequence, including the processing phases initiation (T1), and execution(T2-T6), concatenation(T4). From Abrahamse et al. (2013), p. 3.

initiation. Second is the execution phase (T2-T6, Figure 1), in which the elements in the motor buffer are executed by means of a motor chunk. Finally, longer sequences, consisting of more than five stimuli, seem to show a slow RT in one of the inter-element intervals before the sequence has ended, also referred to as concatenation interval (T4, Figure 1). This is assumed to be due to the division of the entire sequence into more than one motor chunk, as the number of stimuli in the sequence has exceeded the capacity of the motor buffer (Cowan, 2001; Miller, 1956). Concatenation could potentially disappear with practice, when two motor chunks are gradually integrated into a single motor chunk (Abrahamse et al., 2013). The reason behind the concatenation interval is like that of the first stimulus, as this interval indicates the preparation for an upcoming motor chunk (e.g., Abrahamse et al., 2013; Acuna et al., 2014; Bo and Seidler, 2009; Kennerley et al., 2004; Verwey, 2010; Verwey and Wright, 2004; Verwey et al., 2015). An alternative explanation for concatenation is that the sequence was strategically parsed by the participant (Verwey et al., 2009; Wymbs et al., 2012).

The current study used a modified version of the classic DSP task, namely the Dance Step Discrete Sequence Production (DS-DSP) task. In this version the involved effectors are hands and feet, and the input device is a dance mat (Figure 2). Previous research has shown that it is possible to transform experimental motor tasks into tasks that use a different modality than the original experiment. For example, Du and Clark (2018), used a foot stepping serial reaction time (SRT) task, in which the task necessitated whole body actions and changes in posture. Additionally, this task had a larger emphasis on movement execution, because participants would move from a resting position towards the goal-key instead of having their fingers resting on the goal-key already.

1.2. The Cognitive framework for Sequential Motor Behaviour

The C-SMB (Verwey et al., 2015) suggests that there are three levels of cognitive processing at which MSL can develop: the perceptual level, the central level, and the motor level. Representations at the perceptual level result from perceptual processing, and motor representations exist at a motor level. Representations at the central level are not directly related to perceptual or motor processing, and are called central-symbolic representations. These representations are grounded in perceptual and/or motor representations, but are more complex and can include verbal coding (Abrahamse et al., 2013; Fischer and Zwaan, 2008; Goldfarb and Treisman, 2013; Stoet and Hommel, 1999). The distinction between the cognitive processing levels is gradual, as some processes use more than one type of representation. Even though the processing levels are not mutually exclusive from each other, a distinction between processing levels is still important because they can exist independently from each other (Verwey et al., 2015).

At the central level, the central processor is responsible for loading features of the movement into the motor buffer and the short-term memory (STM), this process is also known as motor program activation or parameter specification (Rosenbaum, 1980; Rosenbaum, 1980; Verwey et al., 2015). Through Hebbian learning (what fires together wires together), the repeated use of the features of the single sequence elements together can enable a close association between motor parameters and motor programs. As this association develops, the entire sequence can be loaded into the motor buffer simultaneously by activating a single stimulus (T1, Figure 1). The perceptual processor is responsible at input level, at which there are processors for auditory, visual, and proprioceptive modalities (Verwey et al., 2015). At the presentation of a stimulus, the perceptual processor makes a perceptual representation of the stimulus and makes it accessible to the central processor by loading it into the STM. The representations can consist of the entire sequence, or of several successive representations of parts of the sequence. Pre-processing, extraction of stimulus features, and habitual forms of identification are also responsibility of the perceptual processor. The motor processor executes the content of the motor buffer, and there are separate motor processors for the hands- and feet, as well as for speech (Tattersall and Broadbent, 1991). In the motor buffer are motor representations with concrete instructions for movement, such as the order of execution in the case of a sequence (Verwey, 2001). Additionally, motor representations include how a movement should be adjusted to the bio-mechanics of the effector (Andresen and Marsolek, 2012; Park and Shea, 2003; Verwey and Wright, 2004; Verwey et al., 2015).

Generally, sequences are represented in an effector-independent manner. However, the representation can become more specific to the effector with practice (Abrahamse et al., 2013; Bapi et al., 2000; Hikosaka et al., 1999; Verwey, 2001; Verwey et al., 2009; Verwey and Wright, 2004). This has been demonstrated in previous research by Verwey and Wright (2004), in which participants practiced two sequences with five stimuli each in a DSP task. To execute the sequences, participants used either both hands, or three fingers of a single hand.

With a novel effector [2], execution of the novel sequence was slower compared to execution of the learned sequence, but was faster compared to the execution of a novel sequence by the effector that was initially was used in learning. A later study done by Verwey et al. (2009) in which participants were tested by using the adjacent fingers to the fingers used to learn the sequence, it was suggested that effector-dependent representations can result from effector-based visuo-spatial coding. Additionally, Park and Shea (2003) suggest that adjustment is needed to the bio-mechanical properties of the effector used during learning for effector- specific representations.

1.3. Transfer of motor sequence knowledge

The C-SMB assumes that motor knowledge can be applied flexibly, based on associations between perceptual- and central processing levels (Barnhoorn et al., 2016), otherwise known as transfer of motor sequence knowledge. Transfer of motor sequence knowledge would be indicated by a relatively satisfactory performance of a learned skill, with an unpractised effector. Visuo-spatial representations and motor representations develop simultaneously during learning, however the visuo-spatial representation develops faster than the motor representation (Hikosaka et al., 1999; Verwey et al., 2009). Hence, early in learning sequence execution is based on the visuo-spatial representation and later in learning execution is based on the motor representation. Visuo-spatial representations are effector-independent and attention-driven, and rely on explicit knowledge and working memory, which enables transfer of motor sequence knowledge to unpractised effectors. Motor representations are more founded in effector-specific information in neural motor systems, which are adjusted to biomechanical neurological properties of the effector used (Hikosaka et al., 2002). This information is exploited to optimize execution of the skill and would result in limited transfer of the skill to other effectors (Jordan, 1995; Park and Shea, 2005).

Previous research done on transfer of motor sequence knowledge focused on inter-manual transfer of finger key-press movements (e.g. Verwey and Wright, 2004; Wiestler et al., 2014), finger-movements to arm-movements (e.g. Grafton et al., 1998), or inter-limb transfer using flexion-extension movements with the forearm (e.g. Barnhoorn et al., 2016; Kovacs et al., 2009). Also, transfer has been described along several spectra. Positive transfer

[2] Throughout this study the term 'novel effector' is used to describe any effector that was not involved in the initial learning process of the motor skill or motor sequence.

is when training a skill with one effector, in this case, would facilitate performance with a novel (Müssgens and Ullén, 2015). The opposite is negative transfer, where knowledge learned with one effector disrupts performance with a novel effector. Finally, transfer can be narrow in which the learned motor sequence knowledge is only applicable in a similar task. Otherwise, transfer can be broad, in which the learned motor sequence knowledge can be applied to a broader spectrum of tasks. Additionally, previous research has shown that variable training schedules lead to greater retention of performance and transfer of motor sequence knowledge than blocked schedules of learning (e.g., Shea and Morgan, 1979). This phenomenon is deemed contextual interference, and is assumed to occur because variable practice forces the reconstruction of motor parameters in the working memory at each task switch (e.g., Cross et al., 2007).

1.4. Current study

This study was aimed at exploring the possibility of transfer of sequence knowledge between hands- and feet effectors with a Go/No-Go DS-DSP task, and to understand the sequence representations used by the hands- and feet effectors. The first goal was to explore MSL in the hands- and feet effectors on a block level, as well as on stimulus level. It is predicted that the temporal effects of the DS-DSP task will be comparable to that of a classic DSP task, and that there is no difference between effectors regarding MSL. The second, and more important, goal is to investigate transfer of motor sequence knowledge between the hand- and feet effectors, by comparing the execution of a learned sequence with a novel effector compared to the practiced effector. It is predicted that transfer of motor sequence knowledge will be equal from the hands- to feet effectors compared to the feet- to hands effectors. Furthermore, it is predicted that the transfer will be positive in both directions.

2. Methods

2.1. Participants

Forty students from the University of Twente (32 female, M age = 20.5, SD = 1.78) took part in the experiment in exchange for course credits. All participants were non-smokers, had not consumed alcohol 24 hours prior to participation, and had no physical impairments that would affect performance. The study was approved by the ethics committee of the Behavioural, Management and Social sciences at the University of Twente (ethics number 211415), and all participants signed an informed consent before participation.

2.2. Apparatus

The experiment was programmed and conducted using E-Prime 2.0 on a 24-inch LG Flatron W224422PE DFC full HD monitor set to a refresh rate of 60 Hz. The input device was connected to a laptop with the experiment program running, and unnecessary Windows services were shutdown to avoid any potential delays in RT measurements. A dance mat, as shown in Figure 2, was used as the input device. The arrows on the dance mat were programmed to correspond with spatially comparable placeholders in the experiment program, using Joy- To-Key. The upper arrow on the dance mat was mapped to the 'w'-key which corresponded to the upper placeholder in the experiment file. The bottom, left, and right arrows were mapped to the s-key, a-key, and d-key, which also corresponded to the spatially comparable placeholder on-screen.

Figure 2

Dance mat used as input device for the DS-DSP task. The dance mat (92cm by 81cm) is equipped with a non-slip bottom and no-delay technology (Dancepadmania, n.d.). The placeholders on the screen in are spatially comparable to the arrow.

2.3. Design and counterbalancing

The experiment consisted of a practice phase of 6 blocks, and a testing phase of four blocks. In the practice phase the participants completed the DSP task with either hands or feet as an output modality. Both sequences were presented to the participants during the practice phase 24 times per block, with a total of 144 repetitions per sequence during the practice phase. In the testing phase, each block was a different condition: (1) the learned sequences with the familiar effector (fam/same), (2) the learned sequences with the unfamiliar effector, which is also known as the transfer condition (unfam/same), (3) novel sequences with the familiar effector (fam/nov), and (4) novel sequences with the unfamiliar effector (unfam/nov). The familiar effector is the effector that was used during the practice phase. For a participant who was in the hands group during the practice phase, the familiar effector would be hands and the unfamiliar effector would be feet. The learned sequences are the sequences that were learned by the participants during the practice phase, the novel sequences are sequences that were initially presented during the testing phase. Transfer was measured between the sixth practice block, and the testing condition with learned sequences with the unfamiliar effector. The order in which participants completed the testing blocks was counterbalanced. Participants were allocated to a group (hands or feet) in the practice phase, and an order of testing conditions according to their participant number. The entire counterbalancing scheme can be found in, and an example of the counterbalancing can be seen in Figure 3. The sequences were counterbalanced within- as well as between participants. A fundamental element in the DSP task is that both learned sequences have a different first key, which enables the development of the ability to recognize an entire sequence by the first stimulus. As such, each sequence presented to the participant, the learned and the unlearned sequences, had a different first key. The sequence elements were counterbalanced within the sequence as well. There were four base sequences, of which variations were created through rotation. This resulted in a total of 16 variations of sequences. Various variations of the sequences were tweaked to assure that the difficulty of each sequence was comparable.

2.4. Dance-Step Discrete Sequence Production task

Participants in the feet group completed practice blocks of the DS-DSP task in a standing position, in the middle of the dance mat, participants in the hands group completed the practice blocks in a seated position with both their hands rested on the middle of the dance mat. The viewing distance was about 90 centimetres and 90 degrees from eye-height for both groups. Each practice block consisted of 48 repetitions; each sequence was presented 24 times in random order. In the middle of each block, participants had a 30 second break in which the participants in both groups were instructed to remain in the starting position until the experiment resumed. After each block, participants had a three-minute break, in which they could stretch their legs and have refreshments. However, they were not allowed to do any activities with their mobile phones or read. Each trial consisted of the presentation of one of the two sequences, in the form of a Go/ No-Go procedure. Before the successive stimuli were presented, all placeholders on-screen were empty for a duration of 1000 milliseconds (ms). The stimuli were presented by lighting up a placeholder yellow on- screen for a duration of 750ms per stimuli. When the six successive stimuli had been presented, the participants would receive either a Go stimulus by lighting up the cross in the middle blue, or a No-Go stimulus by lighting up the cross in the middle red. The Go stimulus served as a prompt for participants to reproduce the sequence by pressing the spatially comparable target areas on the dance mat in the seated position, or by stepping in the standing position. The participants were instructed to wait until the cross in the middle had turned white to reproduce the sequence. The No-Go stimulus served as a prompt for participants to remain still and wait until the presentation of the upcoming sequence commenced. The Go and the No-Go stimulus were presented for 3000ms. The No-Go stimulus was presented four times per block, in the practice blocks as well as in the testing blocks. Participants also received feedback about their performance. When participants received a Go stimulus, and reproduced the sequence before the cross turned write, “too early!” was presented on-screen. A new sequence was presented

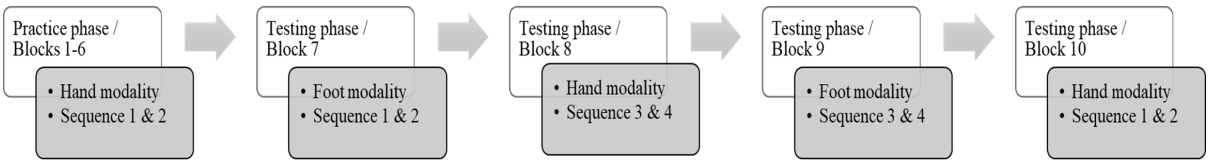

Figure 3

Example of order of blocks in the experiment for a participant. The participant was placed in the hands group in the practice phase and had sequence 1 and 2 as learned sequences. In the first and third testing block the participant used the unfamiliar effector, feet. In the second and third testing block the participant performed the novel sequences, 3 and 4.

immediately afterwards. When participants received a No-Go stimulus and reproduced the sequence, no warning was given. When participants reproduced a sequence correctly, “good!” was displayed on the monitor. In the case of mistakes while reproducing the sequence, participants were told one by one which stimuli were not reproduced correctly.

During the practice phase, participants in the hands group were in a seated position and participants in the feet group were in a standing position for all six blocks. However, during the testing phase participants switched effectors and thus had to switch from standing to seated position, or the other way around. The researcher accommodated the transfer from one position to the other and assured that the viewing distance and viewing angle was the same for both positions. Participants were encouraged to reproduce the stimuli in the manner most convenient to them, there were no specific instructions regarding the use of the left of right effector for certain steps.

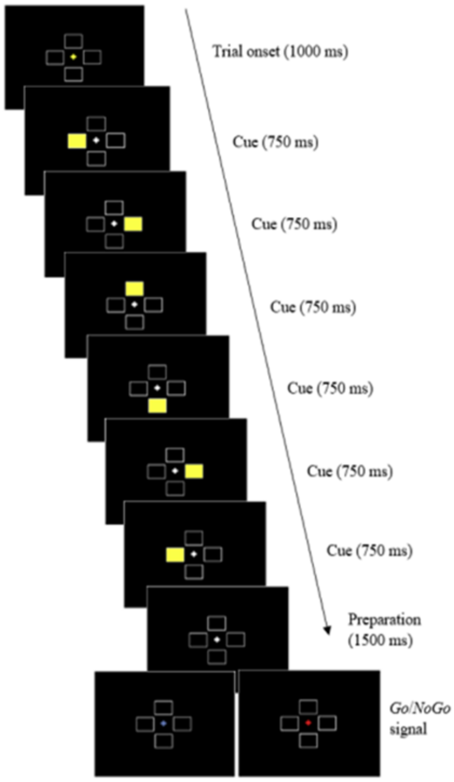

Figure 4

Example of a trial, with the onset, 6 sequences steps and the Go/No-Go signal.

2.5. Data analysis

There are various advantages of the linear mixed model (LMM) approach over the repeated-measures ANOVA, which is the usual approach to analyse DSP tasks. The main benefit of LMMs is that they allow for the specification of random effects as a partition of the variance that is specifically associated with subject- level differences, instead of building this variance into an error term. In other words, in this approach will restrict to the comparisons within the subject, considering innate difference subjects might have regarding physical performance. The RT data were analysed using lmer, from the lme4 package version 1.1.32. (Bates et al., 2015) and the Flexplot package (Fife, 2021), in the R environment 4.2.2.

Prior to analysis, data were processed by transforming them from an E-Prime output file, to .csv using the syntax provided in. The data was then prepared by applying exclusion criteria to improve the accuracy of the models. The total dataset consisted of 19,200 trials. First, all trials with one or more mistakes were removed from the raw dataset, leaving only accurate trials. Second, all trials with a Mean RT 2.5 standard deviation above the mean. The RT was calculated by adding the RT's for each stimulus and dividing them by six per trial. Third, all trials with the sum of the six stimuli RT"s were removed if they were 2.5 standard deviation of the mean.

The first model aimed to understand MSL on a block-level between effectors with Mean RT in milliseconds (ms) per trial as outcome variable. The second model aimed to understand the potential differences between the first response position and a concatenation interval at the third/fourth response position between effectors, with Stimulus RT in ms as outcome variable. The first and second model include data from the practice phase. A third model was aimed at understanding differences in testing conditions between the hands and feet effectors. A final model was aimed to investigate the directionality of transfer. The third and fourth model had Mean RT in ms per trial as outcome variable. The third model included data from the testing phase, and the fourth model included data from the last practice block as well as the transfer condition. The fixed effects Block (1 – 6), Position (1 – 6), and Condition (fam/same, unfam/same, fam/nov, unfam/nov), were within-participant variables, and Group (hands – feet) was a between-participant variable. Furthermore, each model contained a random effect on subject-level. The R-syntax for the models concerning the practice phase can be found in Appendix C, that of the models concerning the testing conditions in Appendix D and that of the models concerning transfer in Appendix E.

3. Results

3.1. Practice phase block-level

Within the model predicting Mean RT with Block and Group, the effect of Block was significant and negative ($\beta = -175.13, 95\% CI[-183.45, -166.80], t(9123) = -41.24, p < .001$), such that both groups showed a reduction in RT across Blocks. There was a significant and negative Group [hands] x Block interaction, ($\beta = -34.05, 95\% CI[-46.31, -21.80], t(9123) = -5.45, p < .001$), such that Group [hands] demonstrated a higher reduction in RT across Blocks compared to Group [feet] (Figure 5). The effect of Group was non-significant ($p = .85$), there were no differences between Group in Mean RT per Block. Post-hoc Tukey tests with Kenward-Roger degrees-of-freedom with Mean RT and Block, and Mean RT and Block x Group interaction were done. Pairwise differences to explore the effect of Block showed that RTs in Blocks 1, and 2 were significantly slower compared to RTs in the ensuing Blocks ($p < .0001$). RTs in Block 3 were slower compared to RTs in Block 5, and 6 ($p < .0001$). RTs

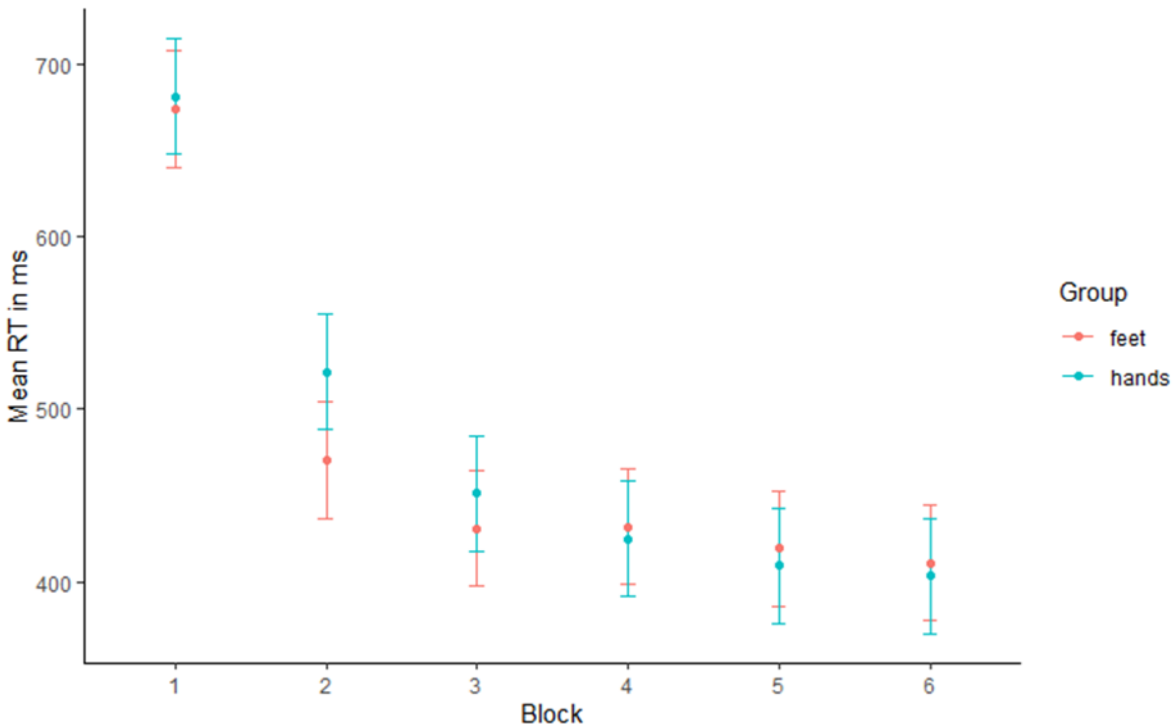

Figure 5

Prediction of Mean RT with Block and Group as fixed factors, and Subject as a random factor. A reduction in RT between the first and sixth Block is clearly visible, with the highest reduction taking place between the first and second Block and the second and third Block.

in Block 4 were also slower compared to RTs in Block 5 ($p = .008$) and Block 6 ($p < .0001$). RTs in Blocks 3, and 4 were not significantly different from each other ($p = .03$) and well as RTs in Block 5, and 6 ($p = .55$).

3.2 Practice phase stimulus-level

Within the model predicting Stimulus RT with Block, Group, and Position the effect of Position is significant, and negative ($\beta = -189.68, 95\%CI[-196.26, -183.10], t(54748) = -56.52, p < .001$), such that there effect of position on RT for across trials. Furthermore, the interaction of Group [hands] x Position was statistically significant and negative ($\beta = -92.47$, $95\%CI[102.21, -82.74], t(54748) = -18.62, p < .001$), such that Group [hands] showed a higher reduction in RT per across trials compared to Group [feet]. Furthermore, the interaction effect Block x Position was significant and positive ($\beta = 85.49, 95\%CI[68.88, 102.09], t(54748) = 10.09, p < 001$) , such that there was an increase in RT across Blocks. Finally, a there was a

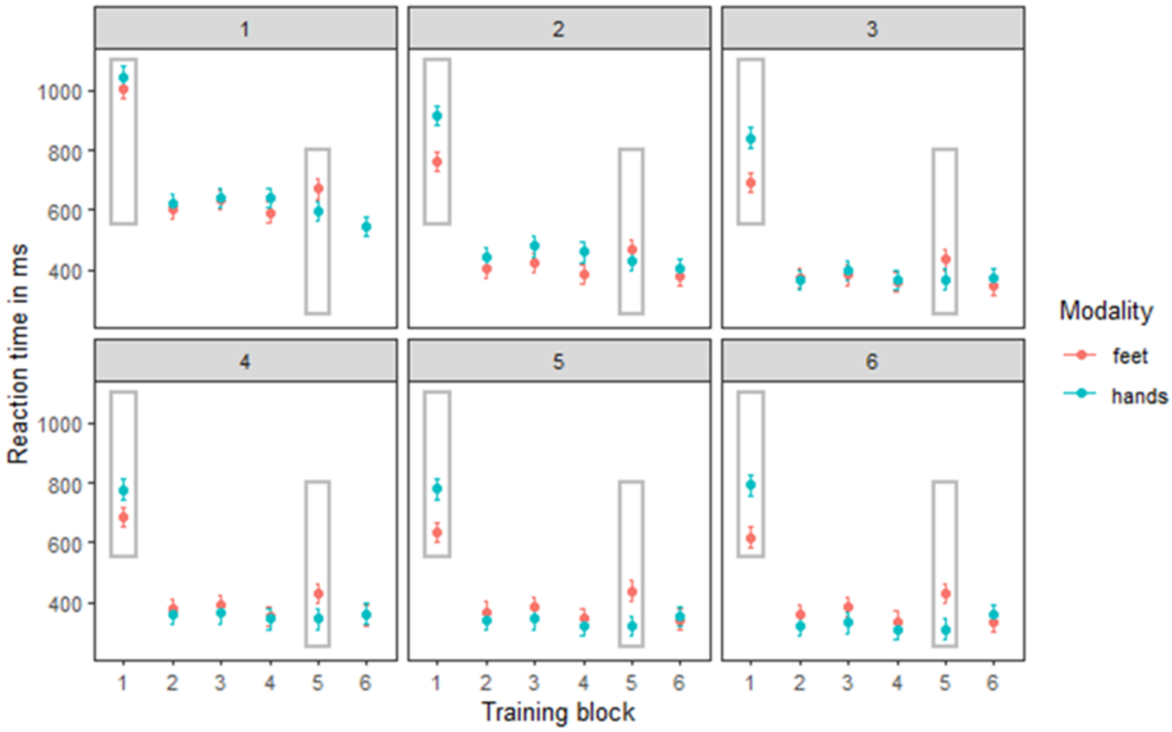

Figure 6

Position per Group and per Block. There is a slight difference, although not significant, that can be seen in Block 5 and Block 6 between Groups. Group [feet] is showing a clearer concatenation interval around Position 5 than Group [hands], but Group [hands] has a slower Position 1 compared to Group [feet].

significant three-way negative interaction effect for Block x Group x Position ($\beta = -39.76$, $95\% CI[-64.25, -15.27], t(57748) = -3.18, p = .001$), such that the interaction on Position between Block x Group is reduced across Position. In other words, the reduction in RT in Group [hands] compared to Group [feet] is less in the latter steps per Block. Post-hoc Tukey tests with Kenward-Roger degrees-of- freedom were done for the main effect of Position. In both groups, Position 1 was slower compared to Position 2 – 6 ($p < .0001$). Furthermore, Position 2 was significantly faster compared to Position 3 and Position 5 ($p < .0001$), and was significantly slower compared to Position 4 and 6 ($p < .0001$). Position 3 was significantly slower compared to Position 4 and 6 ($p < .0001$), but was not significantly different compared to Position 5 ($p = .25$). Position 4 was significantly faster compared to Position 5 ($p < .001$), but was not significantly different compared to 6 ($p = .051$). Position 5 was significantly slower compared to 6 ($p < .0001$).

Additional post-hoc tests were done for the Position x Block interaction. In every Block (1 - 6) Position 1 was significantly slower compared to the ensuing Position 2, 3, 4, 5, and 6 (p < .0001). In Block 1, Position 2 was significantly faster compared to Position 5 ($p = .0006$) and significantly slower than Position 6 ($p = .01$), and Position 3 was significantly slower than Position 6 ($p < .0001$). In Block 2 and 3, Position 3 was faster compared to Position 5 ($p = .05$). In Block 5, Position 3 and Position 4 were significantly faster compared to Position 5 ($p = .002; p < .0001$). In Block 6 Position 3 was faster compared to Position 4 ($p = .03$) and to Position 6 (p = .02). In every Block (1 – 6) Position 5 was significantly slower than Position 6 ($p < .0001$). Post-hoc tests showed that there were no differences between Group for each Position and Block. For example, there were no significant differences between Group [hands] and Group [feet] for Position 1, Block 1 and so forth. Each Position per Block and Group can be seen in Figure 6.

3.3. Testing phase

We fitted a LMM to predict Mean RT with Condition and Effector (hands or feet), and included Subject as a random factor. The model's intercept corresponding to Effector [feet] and Condition [fam/other] is at $365.26(95\% CI[296.65, 433.87], t(4288) = 10.44$, $p < .0001$) Within this model, the interaction effect of Condition [nov/same] on Effector [hands] is statistically significant and positive ($\beta = 144.45, 95\% CI[46.21, 242.70], t(4288) = 2.88, p = .004$) , such that Mean RT was higher for Effector [hands] compared to Effector [feet] in Condition [nov/same]. Post-hoc Tukey tests with degrees-of-freedom method Kenward-Roger with Condition and Effector pointed out that Effector [hands] in the Condition [fam/other] was faster than Effector [hands] in the Condition [fam/same] ($p = .0007$). Additionally, Effector [feet] in the Condition [fam/same] was significantly faster than Effector [feet] in the Condition [nov/other].

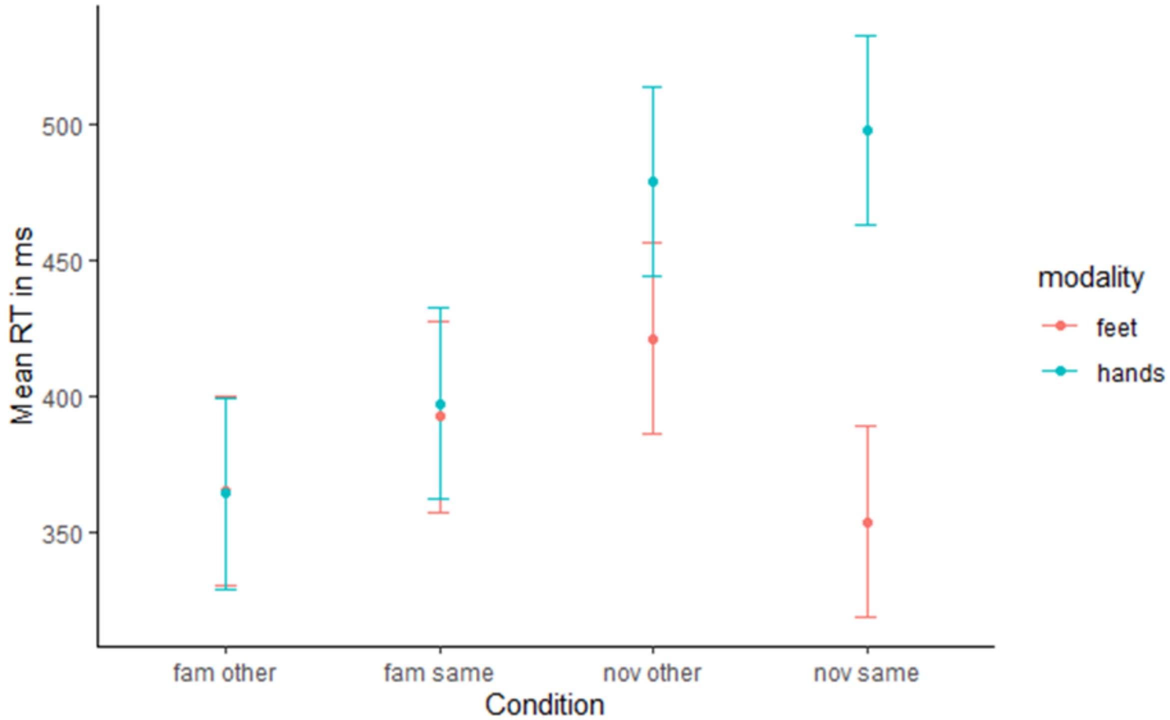

Figure 7

Mean RT per Condition and Group. A significant difference between Groups can clearly be seen in Condition [nov/same].

3.4. Transfer of sequence knowledge

We fitted a LMM to predict Mean RT with Session (training or testing) and the directionality of Transfer (hands to feet [hf] or feet to hands[fh]). The model's intercept, corresponding to Session [testing] and Transfer [hf] is $402.31(95\% CI[315.69, 45.93]$, $t(2713) = 15.58, p < .0001)$. Within this model the effect of Session [training] was statistically significant and positive ($\beta = 17.92, 95\% CI[2.79, 33.05], t(2713) = 2.32, p = .020$). Furthermore, the effect of Transfer [hf] was statistically significant and positive ($\beta = 82.42, 95\%$ $CI[66.29, 98.55], t(2713) = 10.02, p < .0001$). Finally, there was a significant negative interaction between Transfer [hf] and Session [training] ($\beta = -101.20, 95\% CI[-126.5, -75.89]$, $t(2713) = -7.84, p < .0001$). Post-hoc pairwise comparisons showed that RTs in Session [testing] were lower for Transfer [fh], compared to Transfer [hf] ($p < .0001$). Finally, we fitted a LMM to predict Position with Session and Transfer. For Transfer [hf], Position 1 was slower for Session [testing] compared to Session [training] ($p < .0001$), but Position 2 was faster for Session [testing] to Session [training]. For Transfer [fh], Position 1 was faster in Session [training] than Session [testing]. However, for Position 2 – 6 was Session [training] was significantly slower than Session [testing] ($p < .0001$). Within Session [testing], there was no significant difference for Position 1 between Transfer directions. However, for Position 2 – 6, Transfer [hf] was significantly faster than Transfer [fh] ($p < .0001$).

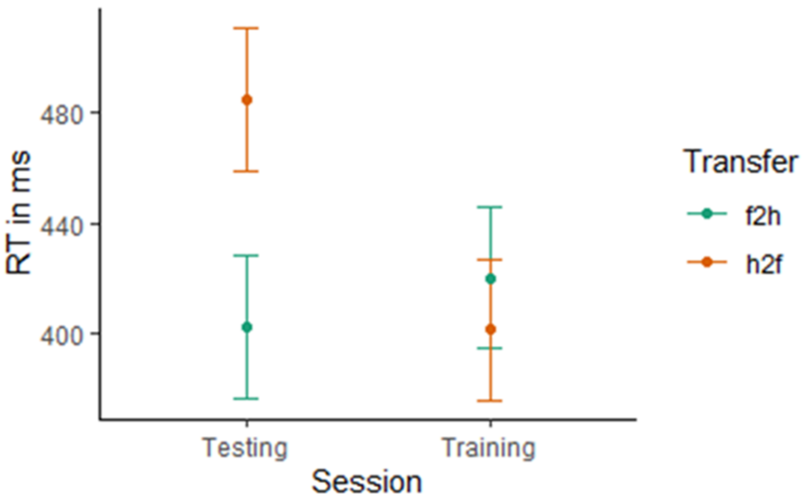

Figure 8

It is clearly visible that there is positive transfer in the feet to hands directionality. However, there is negative transfer in the directionality from hands to feet

Discussion

The purpose of this study was to gain a better understanding of the possibilities of transfer of motor sequence knowledge between the hand- and feet effectors using a DS-DSP task. The results strongly imply that there are differences between effectors. First, from the decrease in RT between blocks it can be inferred that participants learned the sequences, as a decrease in RT is an indication of an increase in performance. Second of all, participants from both groups had a relatively slow RT in the first response, which is in line with previous literature (e.g. Abrahamse et al., 2013; Verwey, 2001), and provides evidence that there is a similar response selection stage for larger movements, specifically with the hands and feet effectors (Verwey, 1999; Verwey, 2001). A visible but non-significant difference between groups was that participants in the hands group had a slower RT to the first stimulus. Previous research suggests that increase in RT to the first stimulus could be an indication of an improvement in performance (Abrahamse et al., 2013). This is because this RT is a temporal representation of the preparation of single sequence elements, and the more elements must be prepared the slower the RT will be. The idea of an improved performance by participants in the hands group is further supported by the lack of a concatenation interval. As suggested by research done by De Kleine and Verwey (2009), the concatenation interval can disappear with practice as two motor chunks might develop into a larger sequence-encompassing motor chunk. Whereas Abrahamse et al. (2013) found the concatenation to be around the fourth sequence element, the present study has shown the initiation of a second motor chunk at the fifth sequence element.

Secondly, significant differences between the hands and feet effectors can be seen when participants were given two new sequences to practice with the same effector they used during the practice blocks. Participants who practiced with the feet effector performed well and integrated the two novel sequences. On the contrary, participants who practiced with the hands effector did not perform the two new sequences as well. A possible explanation for this interference could be that introducing the two new sequences turned the 2-choice RT task into a 4-choice RT task for participants using this effector. Assuming that the participants in the hands modality were already indeed using an effector-dependent representation, this might have caused interference during activation of the motor program and specification of the parameters for the movement (Rosenbaum, 1980; Schmidt, 1975; Verwey et al., 2015). Finally, the results show asymmetry in the directionality of transfer also implies differences in representations of sequence knowledge between effectors after the same amount of practice. The results show that there is positive transfer from the feet to the hands effector, but that there is negative transfer from the hands to the feet effector (Barnhoorn et al., 2016). One interpretation of these findings is that the participants in who practiced with the feet effector used a visuo-spatial representation and that participants who practiced with the hands effector used a motor representation. A visuo-spatial representation would enable transfer and happens early in learning, and a motor representation does not enable transfer well and is used later in learning (Müssgens and Ullén, 2015). The asymmetry might imply that, after the same amount of practice, the participants in the who practiced with the feet effector were still at a relatively earlier stage in MSL compared to participants who practiced with the hands effector. Potentially, because there was less adjustment needed to the biomechanical properties of the hands effector, which in turned enabled the earlier use of an effector-dependent representation (Park and Shea, 2003). Besides our own interpretation of the data, an additional explanation warrants comment. Differences between effectors could have also have been caused by the need to strategically parse the sequence in accordance with any biomechanical factors (Abrahamse et al., 2013; Wymbs et al., 2012). It might be expected especially with execution of sequences in a standing position, in which balance is imminent. If, as the present study suggests, there are differences between effectors in MSL then there is a need for research that explores explicit sequence knowledge at various phases during MSL, as this is an indication of the sequence representation at play. Furthermore, it would be at least interesting to explore the role of the primary motor cortices and supplementary cortices during MSL with different effectors. Much work remains to be done before a full understanding of the extent of MSL within the entire body is established.

Although the generality of the current results must be established by future research, the present study has provided clear support for variations in MSL between effectors. Not only was there a clear difference between concatenation intervals between hands and feet, but there was also evidence for use of different sequence representations between hands and feet after the same amount of learning. The present research, therefore, contributes to a growing theoretical body about how individuals learn sequences, how these sequences are represented and how they are flexibly applied throughout the body.

References

Abrahamse, E. L., Ruitenberg, M. F. L., De Kleine, E., & Verwey, W. B. (2013). Control of automated behavior: insights from the discrete sequence production task. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00082

Acuna, D. E., Wymbs, N. F., Reynolds, C., Picard, N., Turner, R., Strick, P. L., Grafton, S. T., & Kording, K. P. (2014). Multifaceted aspects of chunking enable robust algorithms. *Journal of Neurophysiology*, *112*(8), 1849–1856. https://doi.org/10.1152/jn.00028.2014

Andresen, D., & Marsolek, C. J. (2012). Effector-Independent and Effector-Dependent Sequence Representations Underlie General and Specific Perceptuomotor Sequence Learning. *Journal of Motor Behavior*, *44*(1), 53–61. https://doi.org/10.1080/00222895.2011.645911

Bapi, R. S., Doya, K., & Harner, A. M. (2000). Evidence for effector independent and dependent representations and their differential time course of acquisition during motor sequence learning. *Experimental Brain Research*, *132*(2), 149–162. https://doi.org/10.1007/s002219900332

Barnhoorn, J., Döhring, F. R., Van Asseldonk, E. H., & Verwey, W. B. (2016). Similar Representations of Sequence Knowledge in Young and Older Adults: A Study of Effector Independent Transfer. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2016.01125

Bo, J., & Seidler, R. D. (2009). Visuospatial Working Memory Capacity Predicts the Organization of Acquired Explicit Motor Sequences. *Journal of Neurophysiology*, *101*(6), 3116–3125. https://doi.org/10.1152/jn.00006.2009

Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*, *24*(1), 87–114. https://doi.org/10.1017/s0140525x01003922

Cross, E. S., Schmitt, P., & Grafton, S. T. (2007). Neural Substrates of Contextual Interference during Motor Learning Support a Model of Active Preparation. *Journal of Cognitive Neuroscience*, *19*(11), 1854–1871. https://doi.org/10.1162/jocn.2007.19.11.1854

Dancepadmania. (n.d.). Basic Dance Pad. https://dancepadmania.com/product/basic-dance-pad/

De Kleine, E., & Verwey, W. B. (2009). Representations underlying skill in the discrete sequence production task: effect of hand used and hand position. *Psychological Research-psychologische Forschung*, *73*(5), 685–694. https://doi.org/10.1007/s00426-008-0174-2

Du, Y., & Clark, J. E. (2018). The "Motor" in Implicit Motor Sequence Learning: A Foot-stepping Serial Reaction Time Task. *Journal of Visualized Experiments*, (135). https://doi.org/10.3791/56483

Fife, D. A. (2021). Flexplot: Graphically-based data analysis. *Psychological Methods*, *27*(4), 477–496. https://doi.org/10.1037/met0000424

Fischer, M. R., & Zwaan, R. A. (2008). Embodied Language: A Review of the Role of the Motor System in Language Comprehension. *Quarterly Journal of Experimental Psychology*, *61*(6), 825–850. https://doi.org/10.1080/17470210701623605

Goldfarb, L., & Treisman, A. (2013). Counting Multidimensional Objects. *Psychological Science*, *24*(3), 266–271. https://doi.org/10.1177/0956797612459761

Grafton, S. T., Hazeltine, E., & Ivry, R. B. (1998). Abstract and Effector-Specific Representations of Motor Sequences Identified with PET. *The Journal of Neuroscience*, *18*(22), 9420–9428. https://doi.org/10.1523/jneurosci.18-22-09420.1998

Hikosaka, O., Nakahara, H., Rand, M. K., Sakai, K., Lu, X., Nakamura, K., Miyachi, S., & Doya, K. (1999). Parallel neural networks for learning sequential procedures. *Trends in Neurosciences*, *22*(10), 464–471. https://doi.org/10.1016/s0166-2236(99)01439-3

Hikosaka, O., Nakamura, K., Sakai, K., & Nakahara, H. (2002). Central mechanisms of motor skill learning. *Current Opinion in Neurobiology*, *12*(2), 217–222. https://doi.org/10.1016/s0959-4388(02)00307-0

Jordan, M. I. (1995). The Organization of Action Sequences: Evidence from a Relearning Task. *Journal of Motor Behavior*, *27*(2), 179–192. https://doi.org/10.1080/00222895.1995.9941709

Kennerley, S. W., Sakai, K., & Rushworth, M. F. S. (2004). Organization of Action Sequences and the Role of the Pre-SMA. *Journal of Neurophysiology*, *91*(2), 978–993. https://doi.org/10.1152/jn.00651.2003

Kovacs, A., Mühlbauer, T., & Shea, C. H. (2009). The coding and effector transfer of movement sequences. *Journal of Experimental Psychology: Human Perception and Performance*, *35*(2), 390–407. https://doi.org/10.1037/a0012733

Miller, G. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81–97. https://doi.org/10.1037/h0043158

Müssgens, D. M., & Ullén, F. (2015). Transfer in Motor Sequence Learning: Effects of Practice Schedule and Sequence Context. *Frontiers in Human Neuroscience*, *9*. https://doi.org/10.3389/fnhum.2015.00642

Park, J. B., & Shea, C. H. (2003). Effect of Practice on Effector Independence. *Journal of Motor Behavior*, *35*(1), 33–40. https://doi.org/10.1080/00222890309602119

Park, J. B., & Shea, C. H. (2005). Sequence Learning: Response Structure and Effector Transfer. *The Quarterly journal of experimental psychology*, *58*(3), 387–419. https://doi.org/10.1080/02724980343000918

Rauch, S. L., Savage, C. R., Brown, H. D., Curran, T., Alpert, N. M., Kendrick, A., Fischman, A. J., & Kosslyn, S. M. (1995). A PET investigation of implicit and explicit sequence learning. *Human Brain Mapping*, *3*(4), 271–286. https://doi.org/10.1002/hbm.460030403

Rhodes, B. J., Bullock, D., Verwey, W. B., Averbeck, B. B., & Page, M. I. (2004). Learning and production of movement sequences: Behavioral, neurophysiological, and modeling perspectives. *Human Movement Science*, *23*(5), 699–746. https://doi.org/10.1016/j.humov.2004.10.008

Rosenbaum, D. A. (1980). Human movement initiation: Specification of arm, direction, and extent. *Journal of experimental psychology*, *109*(4), 444–474. https://doi.org/10.1037/0096-3445.109.4.444

Schmidt, R. R. (1975). A schema theory of discrete motor skill learning. *Psychological Review*, *82*(4), 225–260. https://doi.org/10.1037/h0076770

Shea, J. J., & Morgan, R. L. (1979). Contextual interference effects on the acquisition, retention, and transfer of a motor skill. *Journal of experimental psychology*, *5*(2), 179–187. https://doi.org/10.1037/0278-7393.5.2.179

Stoet, G., & Hommel, B. (1999). Action planning and the temporal binding of response codes. *Journal of Experimental Psychology: Human Perception and Performance*, *25*(6), 1625–1640. https://doi.org/10.1037/0096-1523.25.6.1625

Tattersall, A. J., & Broadbent, D. E. (1991). Output Buffer Storage and the Modality of Recall. *The Quarterly journal of experimental psychology*, *43*(1), 1–18. https://doi.org/10.1080/14640749108400996

Verwey, W. B. (1999). Evidence for a multistage model of practice in a sequential movement task. *Journal of Experimental Psychology: Human Perception and Performance*, *25*(6), 1693–1708. https://doi.org/10.1037/0096-1523.25.6.1693

Verwey, W. B. (2001). Evidence for a multistage model of practice in a sequential movement task. *Journal of Experimental Psychology: Human Perception and Performance*, *25*(6), 1693–1708. https://doi.org/10.1037/0096-1523.25.6.1693

Verwey, W. B. (2010). Cognitive processing in new and practiced discrete keying sequences. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2010.00032

Verwey, W. B., Abrahamse, E. L., & Jiménez, L. A. (2009). Segmentation of short keying sequences does not spontaneously transfer to other sequences. *Human Movement Science*, *28*(3), 348–361. https://doi.org/10.1016/j.humov.2008.10.004

Verwey, W. B., Shea, C. H., & Wright, D. W. (2015). A cognitive framework for explaining serial processing and sequence execution strategies. *Psychonomic Bulletin and Review*, *22*(1), 54–77. https://doi.org/10.3758/s13423-014-0773-4

Verwey, W. B., & Wright, D. L. (2004). Effector-independent and effector-dependent learning in the discrete sequence production task. *Psychological Research-psychologische Forschung*, *68*(1), 64–70. https://doi.org/10.1007/s00426-003-0144-7

Wiestler, T., Waters-Metenier, S., & Diedrichsen, J. (2014). Effector-Independent Motor Sequence Representations Exist in Extrinsic and Intrinsic Reference Frames. *The Journal of Neuroscience*, *34*(14), 5054–5064. https://doi.org/10.1523/jneurosci.5363-13.2014

Wymbs, N. F., Bassett, D. S., Mucha, P. J., Porter, M. A., & Grafton, S. T. (2012). Differential Recruitment of the Sensorimotor Putamen and Frontoparietal Cortex during Motor Chunking in Humans. *Neuron*, *74*(5), 936–946. https://doi.org/10.1016/j.neuron.2012.03.038

Appendix A

Counterbalancing for participant allocation

Subject number	Block 1-6	Block 7		Block 8		Block 9		Block 10	
	Modality	Modality	Sequence	Modality	Sequence	Modality	Sequence	Modality	Sequence
1	Feet	Hands	Familiar	Feet	Familiar	Hands	Novel	Feet	Novel
2	Hands	Feet	Novel	Hands	Familiar	Feet	Familiar	Hands	Novel
3	Feet	Hands	Novel	Feet	Novel	Hands	Familiar	Feet	Familiar
4	Hands	Feet	Familiar	Hands	Novel	Feet	Novel	Hands	Familiar
5	Feet	Feet	Familiar	Hands	Novel	Feet	Novel	Hands	Familiar
6	Hands	Hands	Novel	Feet	Novel	Hands	Familiar	Feet	Familiar
7	Feet	Feet	Novel	Hands	Familiar	Feet	Familiar	Hands	Novel
8	Hands	Hands	Familiar	Feet	Familiar	Hands	Novel	Feet	Novel

Appendix B

Syntax for data transformation from .edat2 to .csv

Loading the libraries I need. These are all the libraries for the entire script

```
library(tidyverse)
library(rprime)
library(wrapr)
library(dplyr)
library(tidyr)
library(data.table)
```

Function to read in e-prime text files

```
df_path <- setwd("C:/Data files") #setting working directory
reduce_df <- function(df_path) { #opening the function
  df_lines <- read_eprime(df_path) #telling to "read e-prime" for the wd
  df_frames <- FrameList(df_lines)  #converting the lines into objects
  experiment_df <- to_data_frame(df_frames) #making a dataframe
  dat <- as_tibble(experiment_df) %>%
    select(qc(
      Session, Subject, h, feedback.RTTime, feedback.ACC, feedback.RT #selecting the variables I need from
    ))
  dat <- dat[1:1486, ] #telling where the trials are (this is every line per file)
}

files <- dir(pattern = "*.txt") #telling to look through the directory and take all .txt files
length(files) #checking how many files are in the directory (should be 400)

df <- map_df(files, reduce_df) #creating a data frame from all the files with the function applied to them
names(df) #checking the variable names that are in the data frame
```

Saving data frame as csv

```
write.csv(df, "C:/df.csv", row.names = FALSE)
```

Appendix C

Syntax for cleaning the raw data set

```
{r setup, include=FALSE} knitr::opts_chunk$set(echo = TRUE)
```

```
library(dplyr)
library(tidyr)
library(data.table)
```

Loading the raw dataset

```
df <- read.csv("C:/df.csv")
```

#1. Cleaning the data ##Filling Session & Subject columns

```
df <-
  df %>%
  fill(Session) %>%
  fill(Subject)
```

##Removing any rows that have NA in them

```
df <- na.omit(df)
```

#2. Adding variables for analysis ##ID variable based on Subject number

```
df <-
  df %>%
  mutate(ID = case_when(Subject == 1 | Subject == 9 | Subject == 17 | Subject == 25 | Subject == 33 ~ 1,
                        Subject == 2 | Subject == 10 | Subject == 18 | Subject == 42 | Subject == 34 ~ 2,
                        Subject == 3 | Subject == 11 | Subject == 19 | Subject == 27 | Subject == 35 ~ 3,
                        Subject == 4 | Subject == 12 | Subject == 20 | Subject == 28 | Subject == 36 ~ 4,
                        Subject == 5 | Subject == 13 | Subject == 21 | Subject == 29 | Subject == 37 ~ 5,
                        Subject == 6 | Subject == 14 | Subject == 22 | Subject == 30 | Subject == 38 ~ 6,
                        Subject == 7 | Subject == 15 | Subject == 23 | Subject == 31 | Subject == 39 ~ 7,
                        Subject == 8 | Subject == 16 | Subject == 24 | Subject == 32 | Subject == 40 ~ 8 ))
```

##Phase variable based on ID value

```
df <-
  df %>%
  mutate(Phase = case_when(Session == 1 | Session == 2 | Session == 3 | Session == 4 | Session == 5 |
  Session == 6 ~ 'training', Session == 7 | Session ==8 | Session == 9 | Session == 10 ~ 'testing'))
```

##Step per trial

```
df$step <- c(1,2,3,4,5,6)
```

##Repetition per sequence per session

```
df$rep <- rowid(df$h, df$step, df$Subject)
```

#3. Excluding data ##Trials with at least one incorrect step

```
df1 <- df[df$feedback.ACC != 0, ] #taking out all incorrect steps

df1 <-
  df1 %>%
  group_by(Session, Subject, h, rep) %>%
  mutate(counter = cumsum(step != 21))

df1 <-
  df1 %>%
  group_by(Subject, Session, h, rep) %>% #grouping per repetition
  mutate (var = sum(counter <= 6)) %>% #setting max of the counter to 6
  filter (var > 5) %>% #variable should be less than 6
  select (-var) #exclude

df1 <- select(df1, c(-counter)) #removing counter column
```

##Trials with a mean RT > 2.5 standard deviation above the mean ###Creating dataframe with mean RT per repetition per sequence

```
df2 <- #summarizing data frame over step with mean per trial
  df1 %>%
  group_by(Session, Subject, h, rep) %>% #grouping per trial
  summarise(meanrt = mean(feedback.RT)) #creating mean per trial
```

###Creating dataframe with mean RT per session to determine exclusion criteria

```
df3 <- #summarizing data frame over repetition with mean per session
  df1 %>%
  group_by(Session) %>% #determining sd per session
  summarise(sdrt = sd(feedback.RT), meanrt = mean(feedback.RT))

df3$excl_crit <- (df3$meanrt + (df3$sdrt * 2.5))

df2 <- left_join(df2, df3, "Session")
```

###Excluding trials above the exclusion criteria

```
df4 <- subset(df2, df2$meanrt.x < df2$excl_crit)

df5 <- left_join(df4, df1, by = c("Session", "rep", "h", "Subject"))
```

##Trials with a sum RT > 2.5 standard deviation above the mean

```
df6 <- #data frame summarized over step with sum per trial
  df5 %>%
  group_by(Session, Subject, h, rep) %>%
  summarise(sum = sum(feedback.RT))
```

```
df7 <-
  df6 %>%
  group_by(Session) %>%
  summarise(sdsum = sd  (sum), meansum = mean(sum))

df7$excl_crit <- (df7$meansum + (df7$sdsum * 2.5))

df8 <- left_join(df7, df6, "Session")

df9 <- subset(df8, df8$sum < df8$excl_crit)

df10 <- left_join(df9, df5, by = c("Session", "rep", "h", "Subject" ))
df10 <- select(df10, -c(sdsum, meansum, excl_crit.x, meanrt.x, sdrt, meanrt.y))
```

Adding modality per session #Subsetting into training and testing blocks

```
training <- subset(df10, Phase == "training")
training$modality[training$ID == 1 | training$ID == 3 | training$ID == 5 | training$ID == 7] <- "feet"
training$modality[training$ID == 2 | training$ID == 4 | training$ID == 6 | training$ID == 8] <- "hands"

testing <- subset(df10, Phase == "testing")

ses7 <- subset(testing, Session == 7)
ses8 <- subset(testing, Session == 8)
ses9 <- subset(testing, Session == 9)
ses10 <- subset(testing, Session == 10)
```

Adding modality per block and ID

```
ses7$modality[ses7$ID == 1 | ses7$ID == 3 | ses7$ID == 6 | ses7$ID == 8] <- "hands"
ses7$modality[ses7$ID == 2 | ses7$ID == 4 | ses7$ID == 5 | ses7$ID == 7] <- "feet"

ses8$modality[ses8$ID == 1 | ses8$ID == 3 | ses8$ID == 6 | ses8$ID == 8] <- "hands"
ses8$modality[ses8$ID == 2 | ses8$ID == 4 | ses8$ID == 5 | ses8$ID == 7] <- "feet"

ses9$modality[ses9$ID == 1 | ses9$ID == 3 | ses9$ID == 6 | ses9$ID == 8] <- "hands"
ses9$modality[ses9$ID == 2 | ses9$ID == 4 | ses9$ID == 5 | ses9$ID == 7] <- "feet"

ses10$modality[ses10$ID == 1 | ses10$ID == 3 | ses10$ID == 6 | ses10$ID == 8] <- "hands"
ses10$modality[ses10$ID == 2 | ses10$ID == 4 | ses10$ID == 5 | ses10$ID == 7] <- "feet"
```

Adding relative novelty of the modality per block and ID

```
ses7$rel_effect[ses7$ID == 1 | ses7$ID == 2 | ses7$ID == 3 | ses7$ID == 4] <- "other"
ses7$rel_effect[ses7$ID == 5 | ses7$ID == 6 | ses7$ID == 7 | ses7$ID == 8] <- "same"

ses8$rel_effect[ses8$ID == 1 | ses8$ID == 2 | ses8$ID == 3 | ses8$ID == 4] <- "same"
ses8$rel_effect[ses8$ID == 5 | ses8$ID == 6 | ses8$ID == 7 | ses8$ID == 8] <- "other"
```

```
ses9$rel_effect[ses9$ID == 1 | ses9$ID == 2 | ses9$ID == 3 | ses9$ID == 4] <- "other"
ses9$rel_effect[ses9$ID == 5 | ses9$ID == 6 | ses9$ID == 7 | ses9$ID == 8] <- "same"

ses10$rel_effect[ses10$ID == 1 | ses10$ID == 2 | ses10$ID == 3 | ses10$ID == 4] <- "same"
ses10$rel_effect[ses10$ID == 5 | ses10$ID == 6 | ses10$ID == 7 | ses10$ID == 8] <- "other"
```

Adding relative novelty of sequence per block and ID

```
ses7$test[ses7$ID == 1 | ses7$ID == 4 | ses7$ID == 5 | ses7$ID == 8] <- "fam"
ses7$test[ses7$ID == 2 | ses7$ID == 3 | ses7$ID == 6 | ses7$ID == 7] <- "nov"

ses8$test[ses8$ID == 1 | ses8$ID == 2 | ses8$ID == 7 | ses8$ID == 8] <- "fam"
ses8$test[ses8$ID == 3 | ses8$ID == 4 | ses8$ID == 5 | ses8$ID == 6] <- "nov"

ses9$test[ses9$ID == 2 | ses9$ID == 3 | ses9$ID == 6 | ses9$ID == 7] <- "fam"
ses9$test[ses9$ID == 1 | ses9$ID == 4 | ses9$ID == 5 | ses9$ID == 8] <- "nov"

ses10$test[ses10$ID == 1 | ses10$ID == 2 | ses10$ID == 7 | ses10$ID == 8] <- "fam"
ses10$test[ses10$ID == 3 | ses10$ID == 4 | ses10$ID == 5 | ses10$ID == 6] <- "nov"

testing <- rbind(ses7, ses8, ses8, ses10)

testing$condition <- paste(testing$test, testing$rel_effect)

testing <- select(testing, -c(Phase, test, rel_effect))
```

Writing csv for training data

```
write.csv(training, "training.csv", row.names = FALSE)
```

writing csv for testing data

```
write.csv(testing, "testing.csv", row.names = FALSE)
```

Appendix D

Syntax for the analysis of the data from the training blocks

{r setup, include=FALSE} knitr::opts_chunk$set(echo = TRUE)

```
library (tidyverse)
library(lme4)
library(flexplot)
library(report)
library(emmeans)
library(pbkrtest)
library(lmerTest)
library(effects)
library(writexl)
```

#I. Data preparation ##Opening the training data set `{r Working directory} getwd() {r Original dataset} d_original <- read.csv('training.csv')` ##Rename columns and making Block and Step and ordered factor `{r Dataset for Block level analysis} d <- d_original %>%   rename(Block = Session, Sequence = h,   Repetition = rep,   SumRT = sum,   Step = step,   Group = modality,   StepRT = feedback.RT) %>%   mutate(Block = factor(Block, ordered = T),   Step = factor(Step, ordered = T),   Group = factor(Group)) {r Adding Mean RT as a variable} d <- d %>% group_by(Group, Block, Subject, Sequence, Repetition) %>%   summarize(MeanRT = mean(StepRT)) {r Dataset for Step level analysis} d1 <- d_original %>%   rename(Block = Session,   Sequence = h, Repetition = rep,   SumRT = sum,   Step = step,   Group = modality,   StepRT = feedback.RT) %>%   mutate(Block = factor(Block, ordered = T),   Step = factor(Step, ordered = T))` Hypothesis 1 - Group level differences between Blocks #Setting up the model, with SumRT (trial-levelRT) as dependent variable, #Block and Group as fixed factors, and Subject as a random factor. `{r H1: Full model Block X Group interaction} train_1F = lmer(MeanRT ~ Block * Group + (1|Subject), data = d)` #Making a reduced model without an interaction effect `{r H1: Reduced model without Block X Group interaction} train_1R <- lmer(MeanRT ~ Block + Group + (1|Subject), data = d) {r H1: Comparing full and reduced model} model.comparison(train_1F, train_1R)` ##From these results we can conclude that we should ##use the full model with interaction effect Block X Group #Visualizing the residuals to check if the model can be trusted `{r H1: Visualizing residuals of the full model} visualize(train_1F, plot = "residuals")` ##looks a little asymmetrictal, S-L plot looks good too

```
train_1F
```

#Running an ANOVA on the full model `{r H1: Type III Anova on lmer with Block X Group interaction} anova(train_1F, type='III') {r H1: Reporting on the effects} report(train_1F) {r H1: Post-hoc Tukey tests Block main effect} emmeans(train_1F, list(pairwise ~ Block), adjust = "tukey", pbkrtest.limit = 9137) {r H1: Post-hoc Tukey tests with Block X Group interaction} emmeans(train_1F, list(pairwise ~ Block * Group), adjust = "tukey", pbkrtest.limit = 9137) {r H1: Modelling the full model into a dataset} ae.train_1F = allEffects(train_1F) ae.df.train_1F = as.data.frame((ae.train_1F[[1]]))`

```
p1.ae.df.train_1F = ggplot(ae.df.train_1F, aes(x = Block, y = fit, color = Group)) +
  geom_errorbar(aes(ymin = fit - se, ymax = fit + se), width = .1) +
  geom_line() +
  geom_point() +
```

```
  ylab("Mean RT in ms") +
  xlab("Block") +
  theme_classic()
plot(p1.ae.df.train_1F)
```

Hypothesis 2 - Predicting Mean RT with Group, Block, and Step ##Setting up and fitting the model, with StepRT (step-levelRT) as ##dependent variable, Block, Group and step as fixed factors, and Subject as a ##random factor. `{r H2: Full model Step X Group X Block interaction} train_2F = lmer(StepRT ~ Step * Group * Block + (1|Subject), data = d1)` ##Making a reduced model without interaction effects `{r H2: Reduced model. No interaction.} train_2R = lmer(StepRT ~ Step + Group + Block + (1|Subject), data = d1)` ##Comparing the full model to the reduced model `{r H2: Model comparison} model.comparison(train_2F, train_2R)` ##The bayes factor tells that the models are significantly different from ##each other. The AIC is higher for the model without an interaction effect #Making a second reduced model with only Step X Group interaction `{r H2: Model comparison - Step X Group - Reduced model} train_3R = lmer(StepRT ~ Step * Group + Block + (1|Subject), data = d1) model.comparison(train_2F, train_3R)` ##Here again we see a significant bayes factor, the AIC again votes for the ##reduced model. ##Making a third reduced model with only Step X Block interaction `{r H2: Model comparison - Step X Block - Reduced model} train_4R = lmer(StepRT ~ Step * Block + Group + (1|Subject), data = d1) model.comparison(train_4R, train_2F)` ##Another significant bayes factor, and a higher AIC for the reduced model. `{r H2: Model comparison - Step X Group vs. Step X Block} model.comparison(train_4R, train_3R)` ##Making a fourth reduced model with only Group X Block interaction

```
train_5R = lmer(StepRT ~ Step + Block * Group + (1|Subject), data = d1)
model.comparison(train_4R, train_5R)
```

##The models are not significantly different. Even though the AIC is higher for ##the Group X Block interaction effect model, the Step X Block X Group ##interaction (full model) model will be used as the difference ##is very small regarding the AIC, and the latter will give more information ##regarding H2. `{r H2: Residuals visualization} visualize(train_4R, plot = "residuals")` ##The histogram shows that the residuals look ok. They are slightly skewed to ##the right. The S-L plot also looks normal.

`{r H1: Printing the model} train_2F` #Running an ANOVA on the full model `{r H1: Type III Anova on lmer with Block X Group X Step interaction} anova(train_2F, type='III') {r H2: Reporting on the effects} report(train_2F)`

`{r H1: Modelling the reduced model into a dataset} ae.train_2F = allEffects(train_2F) ae.df.train_2F = as.data.frame((ae.train_2F[[1]]))`

```
p1.ae.df.train_2F = ggplot(ae.df.train_2F, aes(x = Step, y = fit, color = Group)) +
  geom_errorbar(aes(ymin = fit - se, ymax = fit + se), width = .1) +
  geom_line() +
  geom_point() +
  ylab("Mean RT in ms") +
  xlab("Step") +
  theme_classic() +
  facet_wrap(facets = vars(Block))

plot(p1.ae.df.train_2F)
```

{r Post-hoc Tukey test main effect of Step} emmeans(train_2F, list(pairwise ~ Step), adjust = "tukey", pbkrtest.limit = 9137) {r Post-hoc Tukey test Step X Block interaction} emmeans(train_2F, list(pairwise ~ Step * Block * Group), adjust = "tukey", pbkrtest.limit = 54822)

```
emmeans(train_2F, list(pairwise ~ Step * Block), adjust = "tukey", pbkrtest.limit = 54822)

d2 <- d1 %>% group_by (Group, Block, Step) %>%
  summarise(mean_RT = mean(StepRT))
d2

d3 <- d_original %>% group_by (modality, Session) %>%
  summarise(mean_RT = mean(feedback.RT))
d3

d4 <- d_original %>% group_by (Session) %>%
  summarise(mean_RT = mean(feedback.RT))
d4

knitr::knit("Training.Rmd")

rmarkdown::pandoc_convert("Training.Rmd", to = "latex", output = "Training.tex")
```

Appendix E

Syntax for the analysis of the data from the testing blocks

{r setup, include=FALSE} knitr::opts_chunk$set(echo = TRUE)

```
library(tidyr)
library(dplyr)
library(flexplot)
library(report)
library(effects)
library(ggplot2)
library(emmeans)
library(lme4)

options(max.print = 10000)
```

#I. Data preparation ##Opening the training data set {r Working directory} getwd()

```
d_original <- read.csv('testing.csv')
```

{r Original dataset} d <- d_original %>% rename(Block = Session, Sequence = h, Repetition = rep, SumRT = sum, Step = step, Group = modality, StepRT = feedback.RT, Condition = condition) %>% mutate(Block = factor(Block, ordered = T), Step = factor(Step, ordered = T), Group = factor(Group), Condition = factor(Condition))

```
test_1F <- lmer(StepRT ~ Condition + (1|Subject), data = d)
test_1F

summary(test_1F)

anova(test_1F)

visualize(test_1F, plot = "residuals")

report(test_1F)

d1 <- d_original %>%
  group_by(condition, modality, Session, Subject, h, rep) %>%
  summarize(MeanRT = mean(feedback.RT))

test_2F <- lmer(MeanRT ~ condition  + (1|Subject), data = d1)
test_2F

report(test_2F)
```

{r H1: Modelling the full model into a dataset} ae.test_2F = allEffects(test_2F) ae.df.test_2F = as.data.frame((ae.test_2F[[1]]))

```
p1.ae.df.test_2F = ggplot(ae.df.test_2F, aes(x = condition, y = fit, color = condition)) +
  geom_errorbar(aes(ymin = fit - se, ymax = fit + se), width = .1) +
  geom_line() +
  geom_point() +
  ylab("Mean RT in ms") +
  xlab("Condition") +
  theme_classic()
plot(p1.ae.df.test_2F)

emmeans(test_2F, list(pairwise ~ condition), adjust = "tukey", pbkrtest.limit = 9137)

test_3F <- lmer(MeanRT ~ modality * condition + (1|Subject), data = d1)
test_3F

emmeans(test_3F, list(pairwise ~ condition * modality), adjust = "tukey")

ae.test_3F = allEffects(test_3F)
ae.df.test_3F = as.data.frame((ae.test_3F[[1]]))

p1.ae.df.test_3F = ggplot(ae.df.test_3F, aes(x = condition, y = fit, color = modality)) +
  geom_errorbar(aes(ymin = fit - se, ymax = fit + se), width = .1) +
  geom_line() +
  geom_point() +
  ylab("Mean RT in ms") +
  xlab("Condition") +
  theme_classic()
plot(p1.ae.df.test_3F)

report(test_3F)

anova(test_3F)

test_4F <- lmer(StepRT ~ Condition * Step + (1|Subject), data = d)
test_4F

report(test_4F)

test_5F <- lmer(StepRT ~ Condition * Step * Group + (1|Subject), data = d)
test_5F

anova(test_5F)

ae.test_5F = allEffects(test_5F)
ae.df.test_5F = as.data.frame((ae.test_5F[[1]]))

p1.ae.df.test_5F = ggplot(ae.df.test_5F, aes(x = Step, y = fit, color = Group)) +
  geom_errorbar(aes(ymin = fit - se, ymax = fit + se), width = .1) +
  geom_line() +
```

```
  geom_point() +
  ylab("Mean RT in ms") +
  xlab("Step") +
  theme_classic() +
  facet_wrap(vars(Condition))
plot(p1.ae.df.test_5F)

emmeans(test_5F, list(pairwise ~ Condition * Group * Step), adjust = "tukey")

knitr::knit("Testing.Rmd")

rmarkdown::pandoc_convert("Testing.Rmd", to = "latex", output = "Testing.tex")
```

Appendix F

Syntax for the analysis of the data from transfer data

{r setup, include=FALSE} knitr::opts_chunk$set(echo = TRUE) {r Library}

```
library(dbplyr)
library(tidyr)
library(tidyverse)
library(report)
library(effects)
library(emmeans)
library(lme4)
library(writexl)
```

i. Getting the data `{r Original training datset} d1 <- read.csv('training.csv') {r Original testing dataset} d2 <- read.csv('testing.csv')`

ii. Taking variables from both datasets `{r Sixth session from the training phase} d1 <- d1[d1$Session == 6,] d1 = subset(d1, select = -c(sum, excl_crit.y, feedback.RTTime, feedback.ACC, ID, Phase)) {r Familiar/Other condition from the testing phase} d2 <- d2[d2$condition == "fam other",] d2 = subset(d2, select = -c(sum, excl_crit.y, feedback.RTTime, feedback.ACC, ID, condition))`

iii. Putting datasets togeter for directionality analysis `{r Sixth training session + Familiar/Other condition} d3 <- rbind(d1, d2) d3 <- d3 %>% mutate(step = factor(step, ordered = T))`

iv. Adding directionality variable `{r Adding extra variable depending on Session and modality} d3 <- d3 %>% mutate(Transfer = case_when(Session == 7 & modality == "hands" ~ "f2h", Session == 8 & modality == "hands" ~ "f2h", Session == 9 & modality == "hands" ~ "f2h", Session == 10 & modality == "hands" ~ "f2h", Session == 6 & modality == "feet" ~ "f2h", Session == 7 & modality == "feet" ~ "h2f", Session == 8 & modality == "feet" ~ "h2f", Session == 9 & modality == "feet" ~ "h2f", Session == 10 & modality == "feet" ~ "h2f", Session == 6 & modality == "hands" ~ "h2f"))`

v. Differentiating between testing & training `{r Session 6 is Training and the rest are Testing} d3 <- d3 %>% mutate(Session = case_when(Session == 6 ~ "Training", Session == 7 | Session == 8 | Session == 9 | Session == 10 ~ "Testing"))`

vi. Making a dataset with Mean RT per trial `{r Mean RT per trial - Block level} d4 <- d3 %>% group_by(Transfer, modality, Session, Subject, h, rep) %>% summarize(MeanRT = mean(feedback.RT))`

1. Transfer on block level `{r Mean RT with Block and Transfer} transfer1 <- lmer(MeanRT ~ Session * Transfer + (1|Subject), data = d4) report(transfer1)`

```
ae.transfer_1 = allEffects(transfer1)
ae.df.transfer_1 = as.data.frame(ae.transfer_1[[1]])

p1.ae.df.transfer_1 = ggplot(ae.df.transfer_1, aes(x = Session, y = fit, color = Transfer)) +
  geom_errorbar(aes(ymin = fit - se, ymax = fit + se), width = .1) +
```

```
  geom_line() +
  geom_point() +
  ylab("RT in ms") +
  xlab("Session") +
  theme_classic() +
  scale_color_brewer(palette = "Dark2")
plot(p1.ae.df.transfer_1)
```

`{r Post-hoc comparisons} emmeans(transfer1, list(pairwise ~ Session * Transfer), adjust = "tukey", pbkrtest.limit = 9137) {r Making means and sd table} d5 <- d3 %>% group_by (Session, Transfer) %>% summarise(mean_RT = mean(feedback.RT)) d5` 2. Transfer on Step level `{r Step RT with Block and Transfer} transfer2 <- lmer(feedback.RT ~ Session * Transfer * step + (1|Subject), data = d3) report(transfer2)`

```
ae.transfer_2 = allEffects(transfer2)
ae.df.transfer_2 = as.data.frame(ae.transfer_2[[1]])

p1.ae.df.transfer_2 = ggplot(ae.df.transfer_2, aes(x = step, y = fit, color = Transfer)) +
  geom_errorbar(aes(ymin = fit - se, ymax = fit + se), width = .1) +
  geom_line() +
  geom_point() +
  ylab("RT in ms") +
  xlab("Step") +
  facet_wrap(vars(Session)) +
  theme_classic() +
  scale_color_brewer(palette = "Dark2")
plot(p1.ae.df.transfer_2)
```

`{r Adjusting max print option to enable printing all comparisons} options(max.print=1000000) {r Post-hoc of Session by directionality by step} emmeans(transfer2, list(pairwise ~ Session * Transfer * step), adjust = "tukey", pbkrtest.limit = 9137)`

```
d6 <- d3 %>% group_by (Session, Transfer,step) %>%
  summarise(mean_RT = mean(feedback.RT))
d6

write_xlsx(d6,"C:/Users/evelyn/OneDrive - Sigmax/Documents/Evelyns big bad Masters Thesis/Data analyses/d6.xlsx")
```