The Discrete Sequence Production Task in the form of a Step Task: An application of Individual Exponential Learning Curves in Motor Sequence Learning

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Abstract

Motor sequence learning (MSL) plays a substantial role in everyday life and much research has been done in the field. MSL has frequently been investigated using the *Discrete Sequence Production (DSP) task* during which participants reproduce sequences by pressing keys. Most research to date has been focussed on small movements executed with fingers only, rendering the need to validate those findings with large spatial movements involving the whole body. In the present study, the DSP task was transformed into a step-based version. First, the study aimed to extract information about the individual participants' learning process using exponential learning curves. Second, the study aimed to compare the concatenation patterns from the Dance-Step DSP (DS-DSP) task with the usual Key-Press DSP (KP-DSP) task. Participants practised two sequences over eight training blocks on a commercially available dance mat and learning was measured in terms of response time (RT) and accuracy. The results showed that learning was evident in all participants but participants displayed very different learning rates. Three participants showed great improvement during the first blocks of the experiment which resulted in model parameters that could be identified with great certainty, while two participants showed short RT's throughout but did not improve much during the experiment leading to uncertain model parameters. Concatenation, as found with the KP-DSP task, could only partly be observed in the DS-DSP. While the first four keys in a sequence were executed as a coherent chunk, the fifth and sixth response was slowed. It is believed that this is due to an initial acceleration of movements followed by a slowing to avoid jerks and reduce torque, aimed towards a smooth performance. Future research could explore the use of an adaptive and individualised approach through the used of different sequence lengths to challenge learners in the most optimal way.

Keywords: Motor sequence learning, Discrete Sequence Production task, exponential learning curves, concatenation

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1.0 Introduction

Motor sequence learning (MSL) is a substantial part of people's lives. Nearly every daily activity involves the use of motor skills, many of which are executed in an automated manner by retrieving previously learnt motor sequences. Activities such as brushing teeth or driving a car to work are all examples. MSL is a goal-directed activity and in this context, is used to describe the process in which one learns a sequence of movements with the goal being speed, precision and efficiency (Abrahamse et al., 2013). Once the sequence is learned, reproduction usually requires reduced cognitive effort with high efficiency. MSL has been well researched and evidence suggests that a combination of cognitive control functions and autonomous motor control facilitates performance in reproducing motor sequences (Abrahamse et al., 2013). Similarly, a distinction has been made between externally guided and internally guided control when performing sequences. While the former relies on external feedback in cases where people are unfamiliar with the task, the latter is characterised by rapid motor sequence production with less reliance on external cues. This is often believed to be supported by a well-established internalised representation of the sequence and its corresponding movements (Verwey & Abrahamse, 2012).

As the foundation of motor learning is based on information processing, it can be investigated by measurements of response time (RT), movement time and accuracy of the performance (Verwey et al., 2014). Many studies made use thereof and several tasks have been developed for investigating how participants learn and produce a specific set of movements. Two of the most widely known in psychological research are the *Discrete Sequence Production (DSP) task* (Verwey, 1999) and the *Serial Reaction Time (SRT) task* (Nissen & Bullemer, 1987). Traditionally, in these tasks, participants produce quick and simple movements (i.e. pressing keys) in which cognitive processes can be separated from the movement execution itself (Rhodes et al., 2004). However, since daily activities require a combination of complex whole-body movements, there are limitations to which the learning phenomenon of key-pressing tasks can be applied. For example, MSL has been argued to be effector-specific (Barnhoorn et al., 2016), meaning the motor program learnt in one modality, may not necessarily transfer to other body parts. An integral understanding of whole-body MSL is lacking in the field, and therefore should be further investigated.

Several recent studies extended keyboard-based sequence learning tasks to draw more general conclusions about motor learning abilities (Dotan Ben-Soussan et al., 2013; Du & Clark, 2017, 2018; Olivier et al., 2019, 2021). Notably, a study by Du et al. (2017) indicated that children and adults showcased different learning patterns when executing a step-based SRT task. It was found that fewer children were able to demonstrate declarative knowledge of the learned sequences than adults. Also, children showed the most reduction in RT between the learning blocks as compared to adults who showcased a steady reduction in RT during the learning blocks. While Du et al. (2017) put forward the explanation that children have a smaller memory capacity as compared to adults and are therefore unable to develop explicit knowledge of the sequences inhibiting them to improve their performance while doing the task, it also seems likely that adults use a cognitive-based approach to learning and that children learn rather intuitively and motorically during execution. This may imply that children learn faster in a whole-body task as they are using a more bottom-up approach, directly accessing motor cortical loops (King et al., 2010) rather than a top-down control approach like adults (Ward & Frackowiak, 2003). Moreover, Adi-Japhaid et al. (2019) found that children need less practice than adults to retain a learned motor skill long-term which also alludes to different learning strategies. Yet, it is unclear whether adults are able to use the same approach as children when learning a motor skill. Segregating adults based on their performance and comparing the cognitive with the motoric approach may disclose valuable insights.

While other sequence learning tasks have been redesigned to incorporate whole-body movement (Dotan Ben-Soussan et al., 2013; Du & Clark, 2017, 2018), insights of a Dance-Step version of the DSP (DS-DSP) task have yet to be validated. Thus, the goal of this study is to investigate whether individual learning differences in a DS-DSP task can be observed using a non-linear approach. Specifically, individual learning curves will be created to obtain insights into motor learning on an individual basis that may be hidden through aggregated data. Further, it will be investigated whether the results from the DS-DSP are comparable to results from the Key-Press DSP (KP-DSP) task.

1.1 Discrete Sequence Production Task

Verwey (1999) developed the DSP task in order to be able to investigate the processes that support sequential motor skill acqusition. More specifically, the DSP task initially aimed to separate the cognitive processes that initiate a movement from the actualexecution itself during sequence production.

In the standard setting, participants are seated in front of a computer screen and instructed to place four to eight fingers on specific keys on a keyboard in front of them (Abrahamse et al., 2013). Considering a QWERTZ keyboard layout, these are for example y, d, f, g and j, k, l, - for four fingers from the left and right hand, respectively. The computer screen displays as many placeholders (normally squares) as there are fingers placed on the keyboard, corresponding to the spatial positioning of the keys. Then, a fixed series of two to seven stimuli is presented to the participants (Ruitenberg et al., 2014), in that the placeholders light up and participants must respond by pressing the appropriate key. Over time, a learner goes through different learning phases and execution strategies to perform faster and more efficiently (Abrahamse et al., 2013).

It is well known that learners develop associations when practising a motor sequence leading them to be able to respond faster. Four different accounts have been put forward to explain how those associations develop (Abrahamse et al., 2008). First, with unfamiliar sequences, information processing occurs at stimulus-level with much reliance on external feedback. Initially, stimulus-to-response (S-R) mappings are assumed to be in use meaning that information processing occurs at sensory level upon which an appropriate response is selected (Chan, 2018). Second, stimulus-to-stimulus (S-S) mapping refers to the process of forming associations between successive stimulus characteristics such as the location of a stimulus. This process occurs independently from response characteristics. Third, when associations are developed between successive responses and are independent of perceptual impressions this is referred to as response-to-response (R-R) mapping and illustrates the shift from externally guided to internally guided control. Finally, associations can also develop as response-to-stimulus (R-S) mappings. That is, stimuli are anticipated on the basis of previous responses (Hoffmann et al., 2001). Previous research showed that advanced sequence learning is predominantly motor- rather than perceptually-driven that is supported by response-based mapping (Willingham et al., 2000).

1.2 The cognitive control and execution strategies in the DSP task

The development of representations beyond that of S-R bindings is reflected in the different execution modes that learners utilize (Verwey & Abrahamse, 2012). The underlying processes of these modes can be explained by the *Cognitive Framework for Sequential Motor Behaviour (C-SMB)* which assumes processors exist at three different levels (Verwey et al., 2014). Firstly, the perceptual processors are responsible for sensory input and provide information about a stimulus to the central processor. Secondly, the central processor serves as a connector between the perceptual and the motor processor and involves symbolic representations of stimuli and responses. After processing the information it initiates a response and transmits it to the motor processors (Verwey et al., 2014). Finally, the motor processors are responsible for initiating and producing movements to reach a goal (Shaffer, 1991).

During the learning process, learners utilise three distinct execution modes before they are proficient in reproducing a sequence (Verwey & Abrahamse, 2012). Firstly, the reaction mode is common in executing unfamiliar sequences. It is characterized by sustained cognitive control, whereby attention is mainly placed on the stimulus to link it with an appropriate response. Secondly, after sufficient training and experience, associations between successive stimuli develop at perceptual, cognitive and/or motor level. Both modes are thought to be supported by more sensory-based S-S and S-R bindings. This leads to faster execution of the task if stimuli are presented in a familiar order due to an increasingly robust internalised model of the sequence. In reaction mode, the central processor responds to each stimulus individually by selecting a response and providing it to the motor processor while in association mode some short chunks are already developed (Verwey & Abrahamse, 2012).

Finally, the chunking mode is evident after sufficient training and experience with discrete sequences whereby learners can produce the sequences rapidly. In chunking mode, a sequence of successive responses is executed as if it was a single response. The first response in a chunk is executed rather slow compared to the following responses due to the process of identifying the stimulus and selecting the appropriate motor chunk to execute. Yet, there is no need to have explicit knowledge of the sequences (Verwey & Abrahamse, 2012), as the central processor responds to the first stimulus of a sequence and signals for the motor processor to execute the whole motor sequence (Verwey, 2001). Such fast execution relys on R-R and R-S bindings for sequence execution (Verwey & Abrahamse, 2012).

Specifically, three stages have been observed during the execution of a well-practised sequence (Abrahamse et al., 2013). That is, the first key-press is slowed down due to the selection and preparation of the sequence (Verwey, 1999). This initiation time increases with sequence length since increasingly more responses are loaded into the *motor buffer* after stimulus presentation (Sternberg et al., 1978). After sequence initiation, subsequent responses become faster since they have been loaded and responding only requires execution (Verwey, 1996, 1999). Finally, with sequences including more than four stimuli another slow response midway through the sequence has been observed. In a typical 6-key DSP sequence, this is usually at the fourth response (Verwey, 1999; Verwey et al., 2002). This is due to a limited motor buffer capacity and, thus, longer sequences are divided into two or more segments to ensure smooth conduct (Verwey & Eikelboom, 2003). The process of grouping responses to enable cohesive initiation and fast execution is referred to as concatenation and the increase of response time midway through the sequence is thus the concatenation point (Abrahamse et al., 2013).

1.3 Previous work implementing step-based sequence learning

Previous studies showed that sequence learning tasks can be modified into foot-based tasks. For example, the SRT task was modified to better resemble daily tasks. As Du & Clark (2018) point out, this has the advantage of segregating stimulus from motor processes for large spatial movements. Another advantage is that data on movements, such as the position of the centre of mass, can be collected using appropriate technology (e.g. force plate; motion sensor technology). Several studies have successfully modified keyboard based SRT task to step-based versions (Du, 2016; Du et al., 2017; Du & Clark, 2017, 2018; Olivier et al., 2019, 2021; Paul et al., 2018). Strong similarities are apparent between the SRT task and the DSP task in that both involve a series of stimuli presented on a computer screen that participants need to respond to by pressing spatially corresponding keys (Verwey & Abrahamse, 2012). This suggest that the DSP task could also be successfully transformed into a DS-DSP task rendering the possibility to examine differences between the results from the KP-DSP task and the DS-DSP task.

1.4 Latent growth curves in sequence learning

To date, the Analysis of Variance (ANOVA) is one of the predominant statistical methods in MSL research to understand difference between conditions (Dotan Ben-Soussan et al., 2013; Verwey, 2010; Verwey et al., 2011). For example, Verwey et al. (2011) analyzed RT in the DSP task using ANOVAs based on the key position, practice block and age of the participant. While this enabled them to gain valuable insights (e.g., into the processing modes during MSL), ANOVAs have some severe limitations with the most important one being that they depend on an aggregation of data, which results in a loss of information at an individual-level. Averaging data over participants has been criticized to produce distorted results, especially when individual learning rates vary significantly, because the outcome would in many cases not accurately reflect the individual participants (Brown & Heathcote, 2003). Other methods frequently employed in MSL studies are linear regression models such as Ordinary Least Squares Regression (Verstynen et al., 2012) and Linear Mixed-Effects Regression (Chan et al., 2018, 2020). The latter provides an improvement over the ANOVA as subject level random effects can be accounted for with trial level data being utlized.

The present study introduces individual latent growth curve analysis as an alternative method to further understand subject-level differences. While latent growth curve analysis has frequently been used to model learning processes over time (Brooks & Meltzoff, 2008; DeKeyser, 1997) few studies have applied them to data from MSL tasks. One of them, from Acuna et al. (2014), applied exponential curves to the DSP task to understand chunk development. Yet, their focus was not on individuals, but they applied the Bayesian approach to the population resulting in a loss of participant-level information. Besides providing information on differences between learners, growth curves can also account for non-linearity. This is a crucial aspect since learning rates are known to not be steady but to decrease as learning progresses (Freedman, 1987). Growth curves are therefore more realistic as they can model maximum performance by approaching a certain value and not having an x-intercept. Additionally, they can be used to model between-subject differences in within-subject changes and provide a framework to analyse time-series data (Curran et al., 2010). Finally, this method provides additional information in the form of *Rate*, *Amplitude* and *Asymptote* parameters that may be utilized to individualise training such as the amount of training or difficulty in training.

While growth curves have generally been proven useful, there have been discussions about which mathematical function optimally reflects the learning process. The power curve and the exponential curve have been argued to be most appropriate (Daller et al., 2013; Heathcote et al., 2000). Notably, power curves proved to be a better fit for averaged datasets while exponential curves better resembled unaveraged data. As outlined before, unaveraged data is preferred in the present study leading to the choice of exponential learning curves.

1.5 Predictions

Firstly, it is predicted that learners will learn the DS-DSP task, and that latent growth curve analysis would showcase the usual reduction in response times. Secondly, should the latent growth curve analysis be successful, it would be possible to extract three parameters that are useful for understanding individual learning progression (Rate, Asymptote and Amplitude). Thirdly, I aim to showcase that each participant can be ranked and assessed based on their learning parameters and that this information could be useful for providing feedback on designing individual learning approaches. Lastly, I predict that the concatenation pattern that is found in the KP-DSP task will also be observable in the DS-DSP task. Specifically, the first as well as the fourth response is expected to be slowed down due to the loading of separate chunks.

2.0 Method

2.1 Design

In this study, a between-subject design has been implemented as individual differences are investigated. The study was part of a larger-scale study that collected motion-related data which would be the subject of a separate report. The project was approved by the Ethics committee of the University of Twente in the Netherlands.

2.2 Participants

Participants aged 18 to 35 were recruited via the website “Sona System” of the University of Twente, which provides students with course credits in exchange for their participation. Participants were also recruited within circles of acquaintances living inside of a 20 km radius around Enschede in the Netherlands. It was explicitly required for participants to be healthy. Additionally, they should not have a history of neurological, psychological or psychiatric disorders, no alcohol, tobacco or other drug addictions or dependencies, no signs of cognitive impairment as well as no obvious physical injuries or impairments that would affect their performance during the stepping task. Finally, they should not have taken part in similar sequence learning studies in the past. To facilitate participants to learn as best they could during task learning, they were told that they could win a prize based on their performance: €15, €10 and €5 for the first, second and third fastest.

Five participants took part in the study (3 females, average age 22 ±1.87 years; 60% right-footed). Participants were identified as being right-footed (i.e., reacting faster and possibly being stronger with their right leg) by having participants stand straight and slightly pushing them which caused them to take a step forward with their strong foot.

2.3 Dance-step DSP task

During the DS-DSP task, participants stood in the centre area on a commercially available dance mat (Nonslip Dance Pad Version 5 from D-Force). The stimuli in the task included four rectangles that spatially corresponded to four areas on the dance mat (↑,↓, → and ←) and a cross in their middle (See Figure 1). They were presented on a TV screen (LG model nr. OLED77CX6LA) with a size of 77 inches that was positioned in front of the participants at a distance of 1.20 m from the dance mat. The TV screen and the dance mat were connected to a laptop that ran the

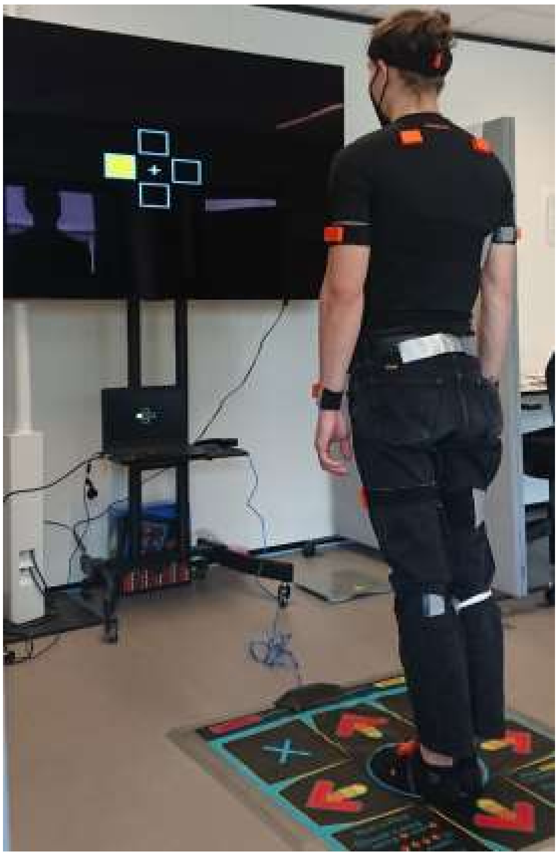

Figure 1. A picture of the experimental set-up. During the DS-DSP participants stand in the centre are of a commercially available dance mat. After six stimuli have been presented to them, they reproduce the sequence by stepping on the spatially corresponding areas on the dance mat.

stimuli of the DS-DSP task. Stimuli were presented using E-Prime Version 2.0.10.356. RT and accuracy measures were collected as part of E-Prime.

Each trial consisted of six stimuli that were presented by a lighting up of the rectangles on the screen. As depicted in Figure 2, first the default screen was presented with a cross in the middle lighting up in yellow for one thousand milliseconds upon which six rectangles took turns in lighting up in yellow for 750 ms each. Next, participants saw the default screen for another 1500 ms after which the cross in the middle lit up in either blue (*Go*) or red (*NoGo*). In the case of a *Go* stimulus, participants needed to reproduce the sequence they had seen by taking six steps on spatially corresponding areas on the dance mat while in the case of a *NoGo* stimulus, the waiting time lasted three seconds until the next sequence was displayed. As outlined by De Kleine & Van der Lubbe (2011), the break during which participants wait for a signal makes it possible to separate motor preparation and action. The frequency of *Go* or *NoGo* stimuli was 92% and 8%, respectively. Participants were given the liberty to organise their responses in the most naturalistic manner. In the case of a mistake, feedback showed which steps were wrong after six steps have been taken. When no mistakes were made, a ‘good’ word was displayed and the next trial was shown.

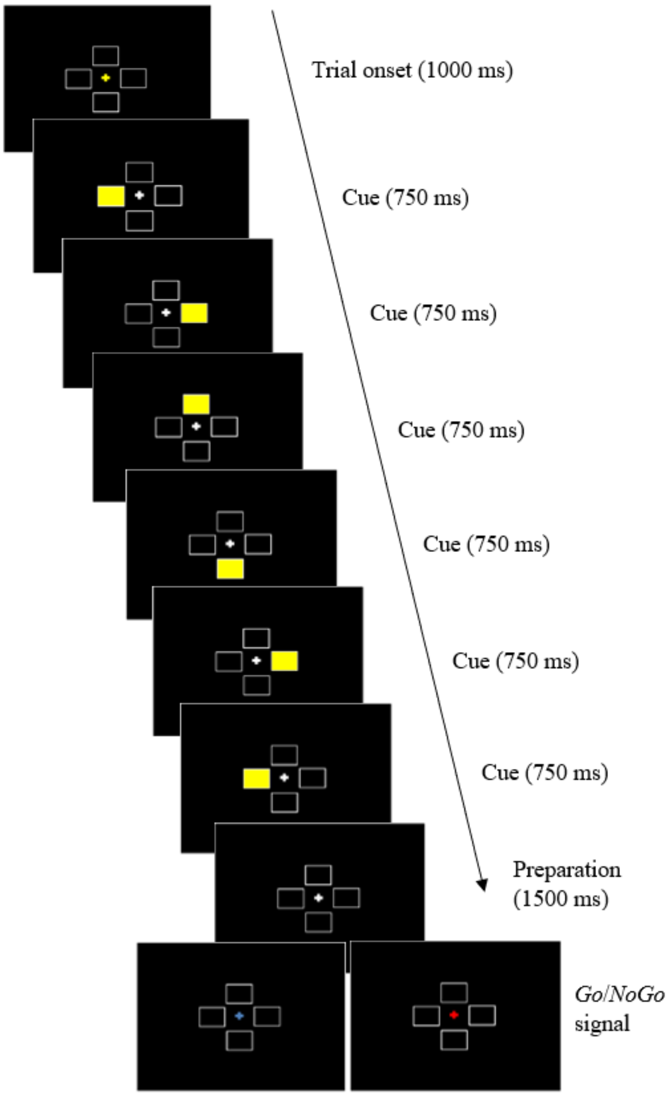

Figure 2. An example of a sequence of stimuli from the onset of stimuli to the Go/NoGo signal. The duration of presentation is indicated for each phase.

Specifically, participants practised the following two sequences: ←→↑↓→← and →↑←↑→↓. To counterbalance foot-specific responses, both sequences were rotated four times resulting in eight different counter-balanced sequences. Participants received different sequences. Thus, possible variations in sequence difficulty or foot strength were expected to not have an effect on the participants' learning process. To give an example, the sequence ←→↑↓→← rotated once resulted in a different counter-balanced sequence ↑↓→←↓↑.

There were eight practice blocks during which participants practised two 6-key sequences. The order in which sequences were presented was randomized but each sequence was practised 12 times per block. After block four, there was a break of 10 minutes. Between all other blocks, there were short breaks of approximately three minutes. Halfway through every block, there also was a 20-second break. Breaks were considered important to avoid physiological and mental fatigue and, therefore, participants were requested to not end breaks early.

2.4 Motion Capture Technology: Xsens

While for the present report only behavioural data regarding RT and accuracy was investigated, data on changes in the centre of mass was also collected for the purpose of another project. This was done by the use of Xsens technology which is a motion capture technology that can be attached to the body (Xsens Inc., 2017). More specifically, sensors were attached to both feet, both lower legs, both upper legs and the pelvis of the participants. Data was then wirelessly transmitted to a computer and loaded into the software MVN Analyze for further analyses (for a review of the MTw Awinda technology see Paulich et al., 2018).

2.5 Procedure

After welcoming participants in the lab, they were briefed about the study, its purpose and their right to leave at any time upon which they provided written informed consent (Appendix A and B). Body measures such as arm span and hip height were taken and entered in the MVN Analyze software for accurate results on the centre of mass movement. Then the Xsens sensors were attached to the participants' body and calibrated by having them walk a straight line. Finally, they were instructed about the stepping task in detail and offered to ask further questions. As there was no way for the software to account for it, participants were explicitly instructed to step with their whole foot during the task and not just with their toes. Preparation for the experiment took approximately 20-30 minutes.

At the beginning of the experiment, participants were asked to stand in the middle of the dance mat and step on the *X* area (top left area) as soon as they were ready. Each block took between 11-15 minutes depending on how fast the participants responded.

2.6 Data Analysis

Before analysing the data, data extraction was performed using Python 3.8. Raw data were averaged per trial. That is, the six RT's corresponding to each step in a sequence were summed up and divided by six to obtain the average RT for each trial (i.e., sequence reproduction). Also, the data were tested for outliers. Since all trials were considered to be conducted accurate and RT's lay within a reasonable range no data were excluded.

Following, learning as measured by RT (s) was analysed using a non-linear mixed-effects model. An exponential learning curve was chosen as a likelihood function. The number of practised repetitions was taken as the independent variable. Analyses were conducted using the statistical programming language R 4.1.0. The model was built using the package brms 2.15.0. A posterior distribution was approximated using Markov-Chain Monte Carlo sampling. An ex-gaussian distribution was fitted to the target variable *RT* and weakly informative priors have been used based on data from previous studies that used whole body stepping tasks (Du & Clark, 2017, 2018). The following formula described by Heathcote et al. (2000) was used for building the model:

$$(1) \qquad y_{pN} = Asym_p + Ampl_p \cdot exp(-Rate_p \cdot N)$$

y: response time
p: participant
N: trial

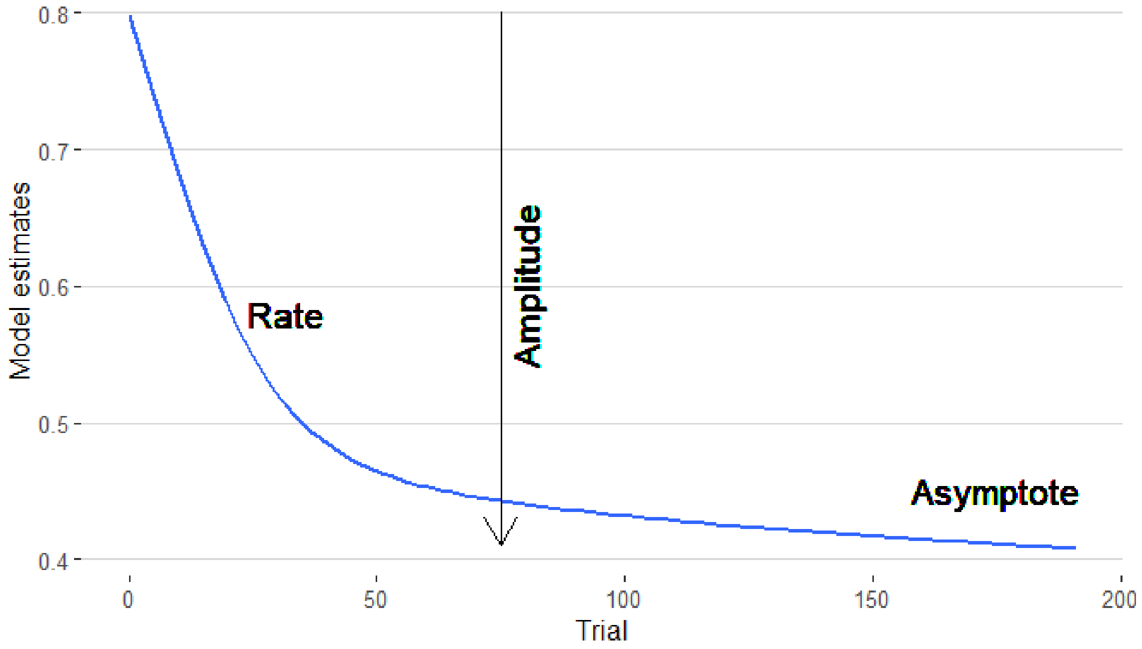

Figure 3. An example of an exponential learning curve. The three key parameters are marked. The *Asymptote* describes the maximum performance, the *Rate* reflects the speed of improvement and the *Amplitude* reflects someone's overall improvement.

The approximate shape of the resulting learning curves is depicted in Figure 3. The *Asymptote* parameter describes the maximum performance that someone could achieve with continuous practice. The *Rate* parameter reflects the speed at which someone improves their performance. The *Amplitude* parameter displays the overall improvement someone makes. Thus, it reflects the distance between someone's initial performance without training and their maximum performance (i.e. Asymptote). The Rate parameter is most informative to the concept of individual learning. The Asymptote is the next most informative as it provides information on the maximum level of learning and therefore the hypothetical amount of training required. The Amplitude carries some ambiguity because a small Amplitude can imply little overall improvement and that a person already had a good performance from the start (e.g. from previous practice), or that the person did not show much learning and good performance in general. The Amplitude although the least informative is still required to create a robust understanding of individual learning.

To investigate concatenation as found with the KP-DSP task, the initial raw dance-step level data was used. Again, no data were excluded from the analyses. Concatenation was analyzed with linear mixed-effects models using the lme4 package Version 1.1-25. In this model, RT in seconds was the response variable with two predictor variables: (1) Dance-Step

Position (1 to 6), and (2) Block (8). Subjects and Accuracy were specified as random factors to account for intraclass correlations. Although plots would be sufficient to understand possible significant interactions between Dance-Step Position and learning Blocks, posthoc Tukey tests were also performed to further ascertain these interactions. For each model, type II Wald chi-square tests were reported to present the significance level of effects for each interaction.

The syntax for extracting data from E-prime text files, cleaning and structuring data, model creation and displaying model output and graphical representations can be found in Appendix C to F.

3.0 Results

3.1 Raw data

To get an initial idea about the learning progress of participants, raw data were inspected. Figure 4 displays the RT's in seconds of all participants throughout the experiment. The two counterbalanced sequences each participant practised are illustrated separately as facets. Every time a sequence was practised was considered as one repetition. To get a better overview and make the graphs comparable, outliers, as defined by those values two standard deviations above the mean and higher, were excluded from the visualizations (mean=0.50, sd=0.39, 2% of data removed for visualization purposes). All participants displayed a learning effect as RT's decreased with an increased number of training trials. Figure 5 shows each participant's progress over the eight blocks of the experiment. Those initial graphs confirm the expectation that learning is not linear but seems to follow the shape of an exponential function.

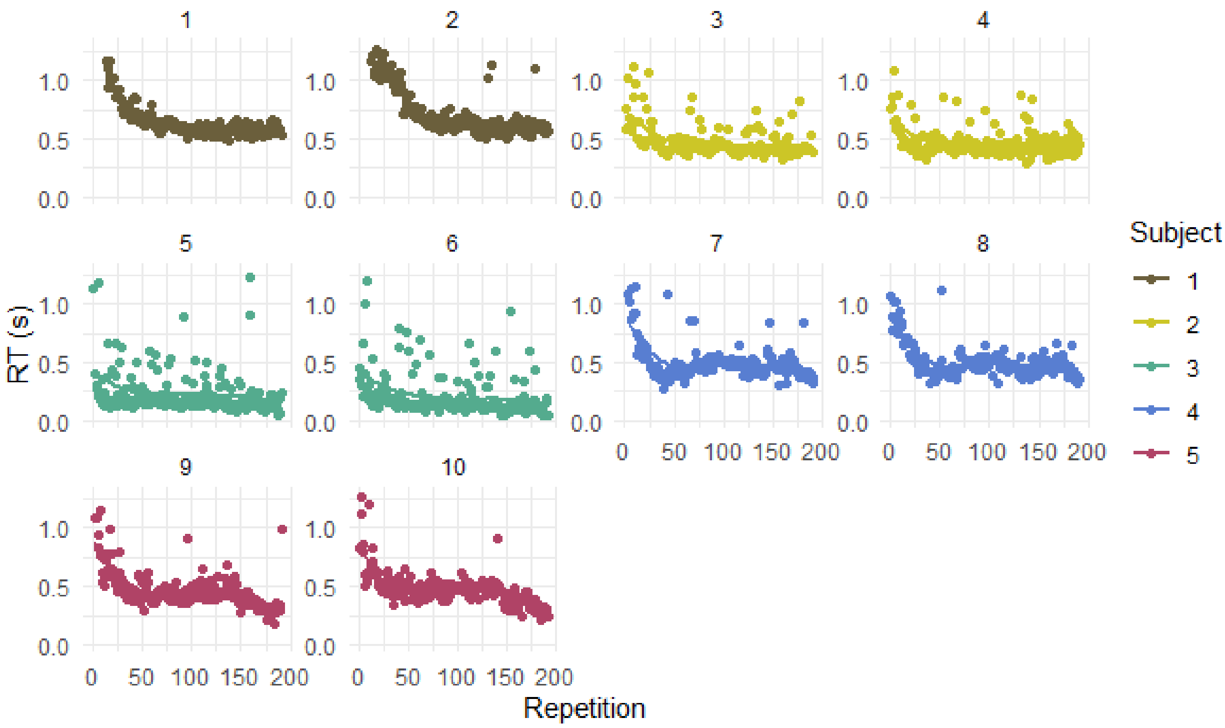

Figure 4. Visualization of raw data. Subjects are indicated by different colours. Each subject practised two different sequences which are illustrated separately. Outliers, as defined by those values two standard deviations above the mean and higher, were excluded for visualization purposes (mean=0.50, sd=0.39, 2% of data excluded). Learning is visible in all participants as RT's decreased with increased repetitions of a sequence.

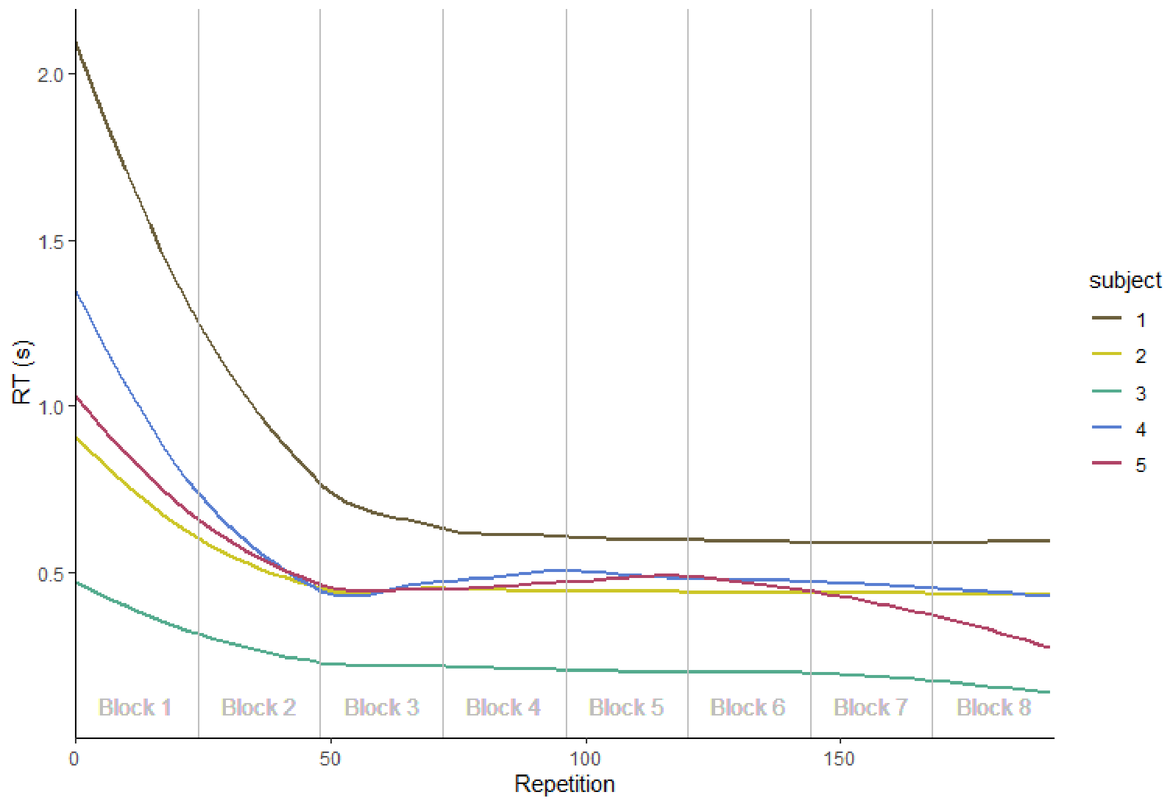

Figure 5. Visualization of raw data across participants**.** Each curve illustrates a participant's RT's in seconds over the eight learning blocks. Learning is visible as for all participants as RT's decreased with increased practice.

3.2 Population average of learning Rate, Asymptote and Amplitude

The non-linear fixed effects model was then computed using the formula previously described (See Formula 1). Table 1 shows the coefficient estimates resulting from the model for the population average of the fixed effect *Trial* rounded to three decimal places. Confidence intervals for all parameters are rather large.

Table 1

Coefficient estimates with 95% credibility limits for fixed effect Trial

Parameter	Centre	Lower	Upper
Rate	0.054	0.010	0.122
Amplitude	0.505	0.142	1.066
Asymptote	0.384	0.139	0.756

Table 2 displays the random factor variation as standard deviation of the parameters. The estimates should be interpreted with caution due to the small sample size. Yet, there is an indication that participants do not have equal possibilities in terms of their maximum performance. Thus, some participants will likely display better performance compared to others after exhaustive practice which is reflected in the Asymptote parameter.

Table 2

Coefficient estimates with 95% credibility limits for the random factor variation

Parameter	Centre	Lower	Upper
Rate	0.057	0.028	0.150
Amplitude	0.432	0.213	1.210
Asymptote	0.294	0.135	1.077

3.3 Learning curves with model estimates

Based on the model estimates, learning curves of individual participants over trials were created. Figure 6a and 6b both display the same estimates for each participant but in Figure 6a scales on the y-axis vary while they are normed in Figure 6b. Also, in Figur 6b data points were added. While all participants display a clear decrease in RT with increased practice, participants differ to a great degree in their learning rate. For example, participants two and four have a steep learning curve followed by a flattening out of the curve as compared to participant five who seems to have a relatively constant learning rate throughout the experiment. The Asymptote (i.e., the maximum performance) of participant five is very difficult to estimate although it does suggest that further improvement can still be gained. The same can be observed for participant three. Yet, it should be noted that participant three starts with a performance that other participants do not even reach towards the end of the experiment. Further, participant one, two and four seem to reach their maximum performance roughly after 50 trials while this can hardly be determined for participant three and five.

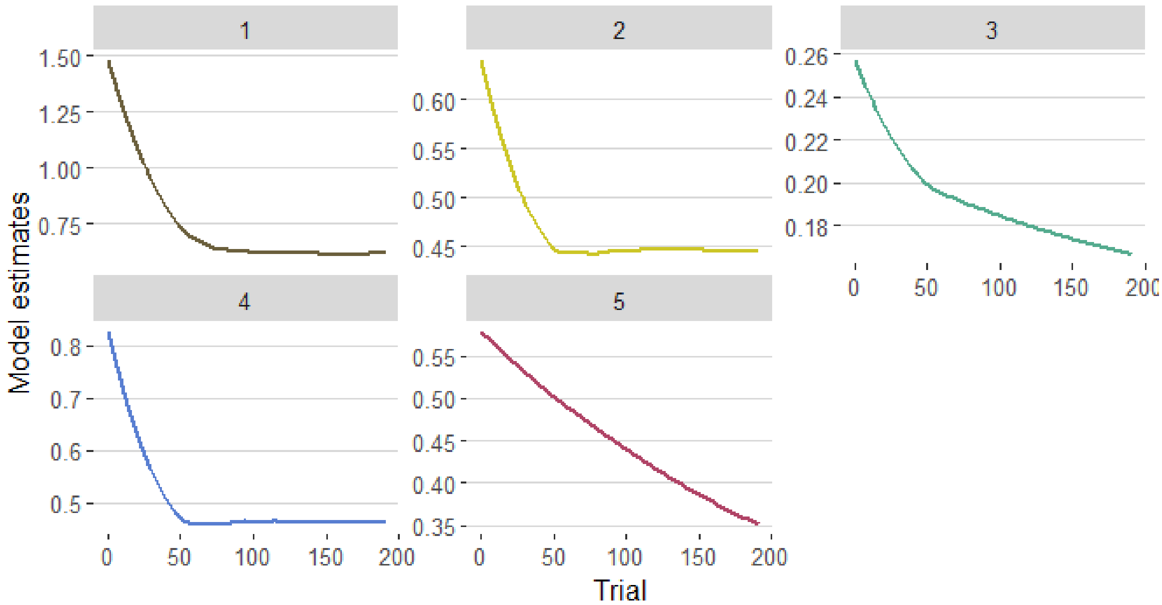

Figure 6a. Visualization of each participant's learning curve based on model estimates. Be aware of the different scales on the y-axis.

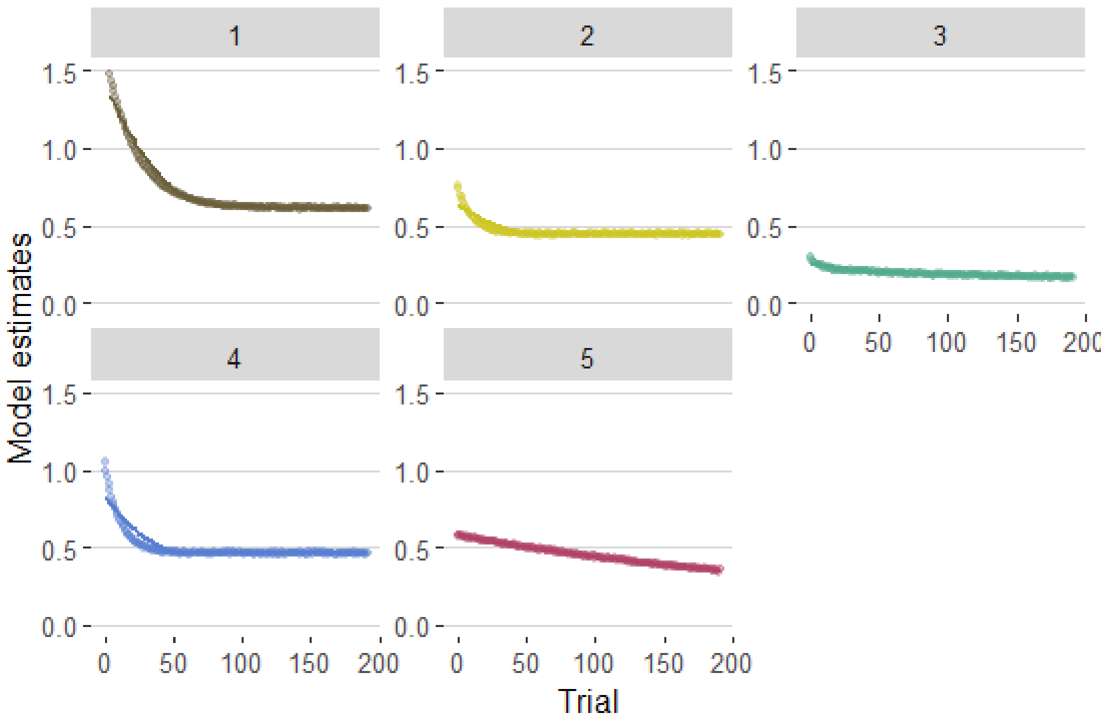

Figure 6b. Visualization of each participant's learning curve based on model estimates with normed y-axes ranging from 0 to 1.5 to ensure comparability. Also, data points were added.

3.4 Individual learning parameters

Following, estimates of the Rate, Amplitude and Asymptote parameters for individual participants were investigated (Figure 7 and Table 3-5). Besides the centre estimates, certainty also varies to a great degree. From the learning curves, it already became apparent that participants three and five are rather slow learners, i.e. they do not improve their performance much during the experiment. This can be confirmed when looking at individual parameters. Their learning Rate is shortly above zero and their Asymptote can hardly be estimated due to a high level of uncertainty. However, the estimate for their asymptote is much lower than for the other participants indicating that their performance is very good even though they do not improve their performance much. Yet, due to the uncertainty of the parameter the inner quartiles of the asymptote for these participants include negative values which is impossible. As the Asymptote is tightly connected to the Amplitude, the Amplitude is also uncertain for participants three and five. In contrast, participants one, two and four display a high learning Rate but seem to have reached their maximum performance early which is reflected in the high certainty of their Asymptote and Amplitude.

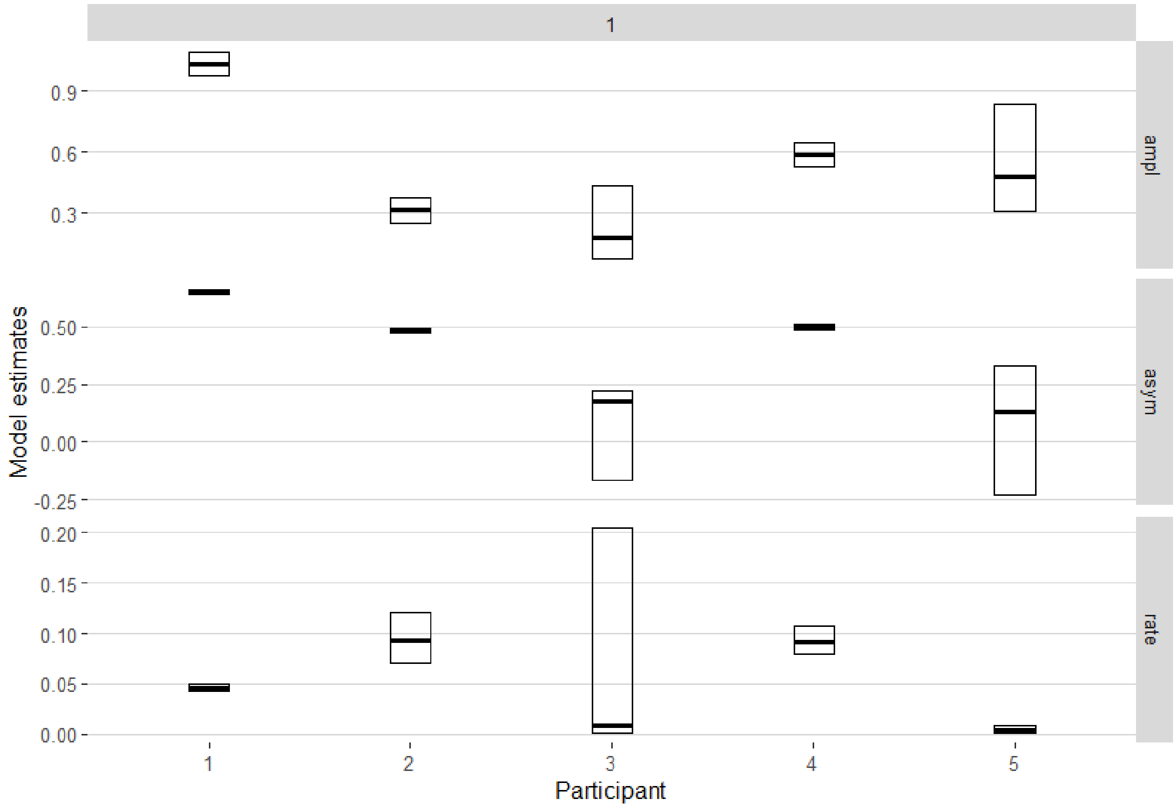

Figure 7. Estimates of the Rate, Amplitude and Asymptote parameters for individual participants. The thick lines represent the median of each parameter per participant. The bars are restricted by the upper and lower bounds of the 95% confidence interval. Thus, shorter bars indicate more certain centre estimates.

Table 3

Coefficient estimates with 95% credibility limits of the Rate parameter for the random effect Participant

Participant	Centre	Lower	Upper
1	0.046	0.042	0.050
2	0.092	0.071	0.120
3	0.008	0.001	0.206
4	0.092	0.080	0.107
5	0.003	0.002	0.008

Table 4

Coefficient estimates with 95% credibility limits of the Amplitude parameter for the random effect Participant

Participant	Centre	Lower	Upper
1	1.034	0.974	1.091
2	0.311	0.246	0.371
3	0.178	0.074	0.433
4	0.587	0.528	0.643
5	0.477	0.305	0.834

Table 5

Coefficient estimates with 95% credibility limits of the Asymptote parameter for the random effect Participant

Participant	Centre	Lower	Upper
1	0.649	0.639	0.660
2	0.482	0.472	0.491
3	0.178	-0.166	0.223
4	0.499	0.489	0.509
5	0.134	-0.232	0.332

3.5 Influence of key position on RT

To test for an effect of stimulus position on RT a linear mixed-effects model was computed which revealed a significant Block x Position interaction on key-press RT, $\chi^2(35, N = 5) = 78.8$, $p < .001$, which showed that RT was changing for each of the positions across learning blocks. Visualizing the effects and interactions (See Figure 8) showed that indeed in general, RT was decreasing for each position for each of the blocks. The posthoc Tukey tests for each position across blocks revealed that this significant interaction was a result from the differences, in that Position one always had longer RTs compared to Position two, three and four ($p < .05$). Position one exhibited similar RTs to the other Positions only by Block eight. However, Position one had a significantly longer RT compared to Position four throughout all eight learning Blocks. Also, in block eight, Position four showed significantly shorter RTs than Position six. Full contrasts between key positions can be inspected in Appendix G.

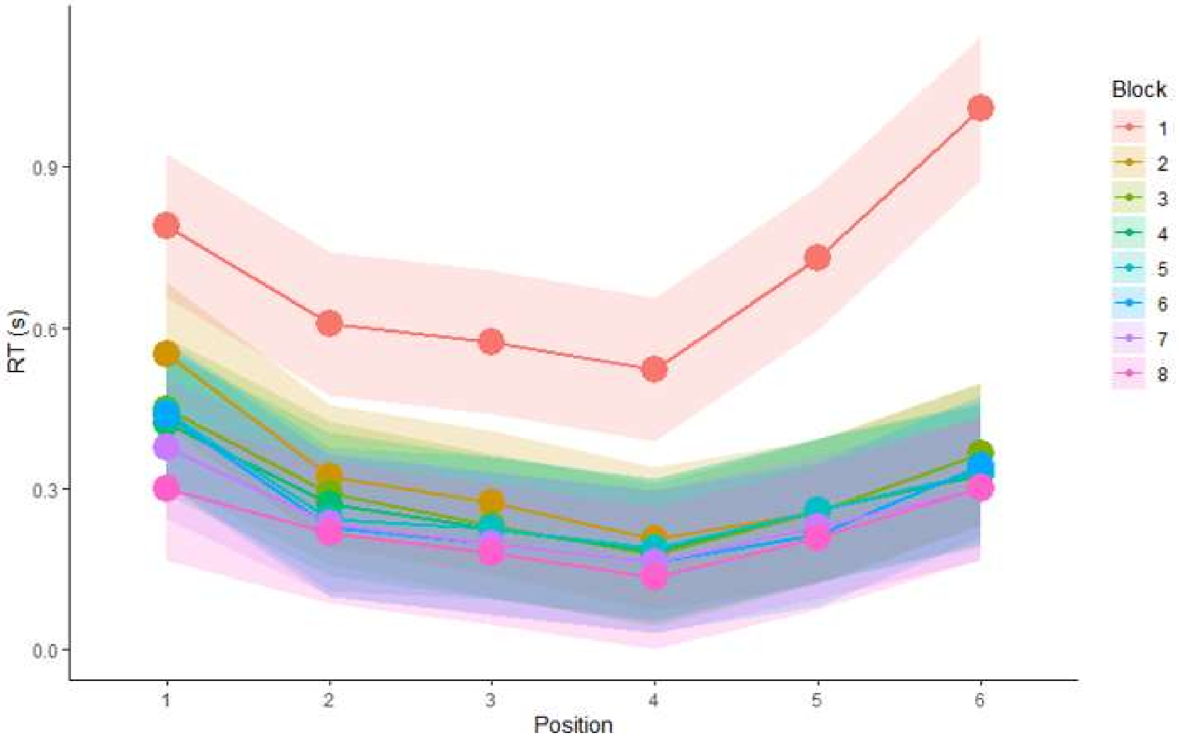

Figure 8. Visualization of estimated RTs in seconds per key position for each block.

4.0 Discussion

In this study, the traditional DSP task was transformed into the DS-DSP task. The first aim of the study was to examine the information that can be extracted from individual learning curves if applied to data collected from the DS-DSP task. Overall, the expectation that learning would be evident in all participants (i.e., RT decreased with increased practice) was confirmed and learning curves mostly displayed the expected shape of an exponential function. The non-linear mixed-effects analysis resulted in multifaceted results.

First, it could be observed that learning differs to a great degree between individuals as reflected in individual learning parameters and their corresponding certainty. Some learners have a rather steep learning curve reaching their maximum performance early, while others have a flat learning curve, suggesting more training for them to reach their maximal performance. In this study, specifically the learning curves of participant three and five showed to be rather flat and less curved while their performance was faster than that from other participants. In contrast, participant two and four had a steep curve reaching their highest possible performance roughly at trial 50 already which is the beginning of block three. Participant one reached their maximum performance roughly at trial 60. Thus, it can be said that those three participants are quick learners which is also reflected in the centre estimates of their Rate parameter since they are considerably higher than the estimate for participant three and five. Also, the Asymptote and Amplitude parameters of participant one, two and four could be estimated with sufficient certainty. The fact that participant three and five did not show much improvement throughout the experiment had a considerable effect on the certainty of the results obtained as all three parameters have large 95% confidence intervals for those participants. There is one exception, namely the rate of participant five which has a small confidence interval. It seems like the participant displayed a steady decline in RT leading to the modelled learning curve approximating a linear shape.

However, learning ability should not be equalized with performance. That is, participant three and five who seem to be slow learners, in fact, displayed the shortest RT's throughout all blocks. Particularly, participant three demonstrated RTs in the first block already that other participants did not even reach towards the end of the experiment. Notably, neither accuracy nor cognitive workload measures were included in the analyses which is why it cannot be concluded that participant three and five are better performers than the other participants. They might have made more errors or put more effort into the task than the other participants. Assuming that the number of errors and the degree of mental worklaod was equal for all participants, one plausible explanation is that that participant three and five had previous training. Even though it was requested from participants that they did not recently take part in any other motor learning studies, they might exercise a sport that requires them to learn motor sequences such as dancing. They might have been very close to their maximum performance at the beginning of the study already which resulted in an uncertainty of the model parameters. This explanation seems likely as their learning curves seem to be shifted. Another plausible explaination would be that participant three and five are naturally talented so improvements are very incremental but significant compared to the faster rates shown by other participants. They might not have reached their maximum performance during this study and additional trials would still be advantageous. Even though this interpretation seems unlikely it should not be disregarded.

While there is some uncertainty about the maximum performance of participants three and five, the results suggest that participants one, two and four overlearned the sequences. These individual differences call for an adaptive design of the study, especially, when the learning rates of participants vary a lot. While sequence learning tasks such as the DSP and SRT task have previously adhered to a static design, it seems advantageous to adapt the number of trials as well as sequence length during the task based on the participants' learning progress. This is not a new idea as previous studies have suggested adaptive approaches to save time and costs while increasing the insights gained from a study. For example, Myung & Pitt (2009) developed such an approach using Bayesian decision theory and highlight the need for a design that renders a model with high certainty on the model parameters. As could be observed in the present study, learning curves were very useful to extract information on individual participants. For those showing considerable improvement during the task confidence interval ranges were as small as 0.02. Thus, intermediate model computation including a predefined stopping rule may provide the advantage of shortening the task for fast learners and extending it for slower learners to gain more certain insights. Yet, extending the task should be treated with caution as fatigue is known to adversely affect performance (Carron & Ferchuk, 1971) and is expected to increase the longer the experiment lasts. Also, in a study conducted by Du et al. (2017) involving the SRT task, children showed the most reduction in RT between learning blocks as compared to adults who displayed a constant decrease in RT. Thus, some cognitive strategies may inhibit the participant to improve their performance during the task. This implies that there should be a limit to the extension of the experiment as some improvements in performance may only become visible after an extensive break. Having participants come back one day later renders the possibilities to overcome these constraints.

Further, adjusting the task by gradually extending the sequence lengths would be a suitable approach to assess the participants' maximum performance which would be reached as soon as RTs significantly increase. If participants three and five indeed approximated their maximum performance in the first block already, RTs only reflect their physical capacity while their cognitive capacities were not exhausted. Previous research found that with increased practice participants utilize different cognitive strategies and tend to use longer chunks (Abrahamse et al., 2013). Thus, it might be that participant three and five are able to use longer chunks than other participants leading them to respond faster. Increasing the sequence length may open up the possibility to provide skill-level appropriate training and uncover those participants' full potential while possibly also leading to more certain parameter estimates.

The second goal of the study was to investigate differences between response times for different step positions in the sequence and compare the results to that of KP-DSP task. It was found that participants seemed to switch to the chunking mode very fast. This was indicated by the fact that, from the first block, response times decreased up to key position four and increased at key position five and six. In block eight, key position four still displayed significantly faster RTs than key position one and six but all other significant differences in RT disappeared. These findings point to the fact that the first four responses were executed as a coherent chunk while the slowed RT at response five and six points to a different strategy.

Those findings display a different concatentation pattern than was found with the KP-DSP task. Usually, the first response of familiar sequences is slowed down because a chunk of responses is loaded into the motor buffer and is followed by responses that are executed very fast. In sequences exceeding four stimuli, the sequence is split into two or more chunks indicated by another slow response midway through the sequence. Considering 6-key sequences, the fourth response is usually slowed (Verwey, 1999; Verwey et al., 2002). A notable difference between the KP-DSP task and the DS-DSP is the number of effectors corresponding to the target positions. While in the traditional task there are four to eight fingers used for four to eight response keys, respectively, in the DS-DSP task participants use two legs to reach four response keys on the dance mat. This requires them to be more flexible as they need to choose a foot and the optimal movement to reach the target which possibly incorporates different undiscovered cognitive strategies.

Previous research found that people frequently develop a motor rhythm when learning a sequence which may deliver an explanation for the findings in the present study (Sakai et al., 2004). Those rhythms can be sequence-specific or be developed independently from the sequence. In the present study, all participants seemingly displayed similar RT patterns across key positions pointing towards an inherent rhythm of the sequence. But given that the same patterns are found across two different sequences that are also counterbalanced this explanation does not seem plausible.

Rather, movements in the DS-DSP seem to follow a "bell-shaped velocity profile" (p.38) as outlined by Rosenbaum et al. (1995). That is, movements start rather slow, then accelerate and slow down when approaching the target. The phenomenon has been found in movements of the shoulder, elbow, wrist and even the eye (Abrams, 1994; Lacquaniti & Soechting, 1982) and has been explained by various factors such as an intended reduction of jerk and torque (Flash & Hogan, 1985; Uno et al., 1989). In the DS-DSP task, participants stay in motion until the end of the sequence. Thus, the execution of one sequence seems to involve the grouping of several movements into one bigger movement. Likely, RT's have not been found to be bell-shaped in the KP-DSP task because it only involves small movements where excessive jerks do not play a role and there is not much force that would need to be reduced when approaching the target (the last key). Future research should evaluate this explanation by examining whether RT's across key positions still display a bell shape when sequences are extended. It is probable that chunks will be observable and that there is a slowing down towards the end of the sequence.

4.1 Limitations

A first limitation to note is the small sample size. Since the study was conducted within a short timeframe, data collection was terminated after data on five participants were collected. Having data from a bigger sample would render the possibility to draw general conclusions about MSL. Particularly, participant three and five displayed unexpected but similar learning patterns while participant one, two and four also showcased similar learning patterns. Thus, it remains undiscovered whether these are, for example, typical patterns for learners with previous practise and those without, or whether there is a variety of learning patterns that were not reflected by the data collected in this study. Future research could build up on this. Notably, the present findings highlight the advantage of learning curves over other statistical methods as the two learning patterns would remain hidden when aggregating data.

Next, to ensure that participants could be recruited within a reasonable time, the study was conducted on a single day. Yet, this prevented the possibility to study consolidation of the learned sequences which could have been achieved by having participants come back on the next day to investigate whether they had retained the learned sequences. Adi-Japhaid et al. (2019) found that consolidation is not similar for everyone which points to different learning strategies and thus should not be omitted when studying the learning progress. Nonetheless, this study gives valuable insights into short-term processes of learning.

Further, the differences in learning rate between participants caused some participants to overlearn the sequences while others possibly were not able to reach their maximum performance. The former case is believed to not have a negative effect on the results. Nonetheless, more data than needed was collected from participant one, two and four and it is possible that participants became bored which may have decreased their performance towards the end. In contrast, it still remains unclear whether participants three and five would have been able to further improve their performance.

4.2 Future research

Future research could investigate adaptive/individualized training designs of the DS-DSP task to optimize learning. Specifically, this can be achieved by intermediate model computation. As participant one, two and four reached their maximum performance at the beginning of block three, future researchers could compute a non-linear mixed-effects model using data from the first three blocks while participants execute block four. Based on the centre estimate of the Asymptote parameter and its certainty, the results could determine whether additional trials are necessary based on a predefined stopping rule. Further, future studies should increase sequence lengths when observing a learning pattern like this of participant three and five. Incremental steps could be incorporated into the task. For example, at first, participants could be given 6-key sequences which are extended by one element at a time up to twelve elements. As soon as RT's significantly increase the participant's maximum performance is reached and extending should be stopped. This way, cognitive control and motor learning abilities could be optimally challenged and the results would be optimsed. Finally, extending the sequence lengths also renders the possibility to examine whether RTs across key positions still display a bell shape or that new concatenation points are found compared to the present study.

4.3 Conclusion

Learning curves provide many possibilities to investigate individual patterns and requirements for effective learning. Computing learning curves can be useful in practice to optimally improve performance while allowing time for consolidation in populations that perform a lot of precision manual tasks such as machine operators, surgeons, athletes and musicians. The duration needed for practice could be determined early in the process and thus training could be delivered most effectively.

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Appendix A

Participant Information Sheet

Research Project Title: Dance-step motor sequence learning

This project has been approved by the University of Twente's Behavioral, Management and Social sciences (BMS) Ethics Committee No. 210390.

Researcher Contact details:

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Invitation to participate in the study: You are invited to participate in the following research study that will investigate how motor sequence learning is reflected in dance-step manner. Participation in this study is strictly voluntary with informed consent required before you begin. You can withdraw your participation from this research study at any time without any consequence to you.

Purpose of the study: This study is designed to investigate reaction time and centre of mass movement when one is learning a new motor sequence. The study will only involve coming to the laboratory for 1 testing session to record your data during practice. This will be completed on a computer involving a step task while your reaction time as well as your movements are recorded using 7 Xsens motion capture sensors fixated on your legs, feet and pelvis.

Eligibility to participate: In order to participate, you must meet the following eligibility criteria:

- You are healthy and aged between 18 and 35 years
- You are not currently taking any prescribed medication on a regular basis (oral or implanted birth contraceptives are ok)
- You are not physically injured
- You do not have any learning disabilities or diagnosed mental health issues or any neurological disorders (such as Alzheimer's, Parkinson's, Stroke, Multiple Sclerosis, Brain tumor, Physical Brain injuries, Seizures or previous concussion/coma)
- You have not previously taken part in any motor learning experiments involving sequence learning tasks in the BMS or via SONA.
- You can attend one session of data collection for up to 4 hours.

- You do not mind having motion capture sensors attached to your legs, feet and pelvis.
- You are not feeling unwell in general.

Interested participants will be screened for eligibility by a researcher prior to participation once more.

Requirements: Participation in the study involves attending a laboratory session ONCE for up to 4-hour research – with up to 4 SONA Credits will be give.

What is Xsens and how is this data collected? The Xsens gear is a 3D motion capture program that uses inertial sensors based on the miniature MEMS technology. Xsens inertial sensor technology will be used for orientation, velocity and positioning data.

Lab Session (~4 hour): In the first session, you will first be asked to provide information about your demographics such as age, education status etc. After this, your body measurements will be taken and entered in the MVN analyze software. Following, you will be fitted with the xsens sensors which communicate wireless with the Awinda base station, which is connected to the stimulus PC. Once the equipment is setup and you are ready, you will be asked to perform a calibration routine that consists of standing still, walking in a straight line, turning around and walking back. This lasts about 5 to 10 minutes. After this, you will perform a step-dance task in which you train motor sequence and a testing block. Halfway through the training blocks, you will be given a 10 minute break and provided with some sweets and a drink. Upon completion of the testing block, you will be assisted in taking the sensors off. To complete the session, you will be debriefed and thanked for your participation.

Risks and benefits: This research study does not involve any risk to your well-being beyond what would be expected from typical daily activities.

Reporting and maintenance of data and participant information: All records containing personal information (i.e., signed written consent form) will remain confidential and no information which could lead to identification of any individual will be released unless required by law. All of the research data in this study is recorded by a unique number, meaning that your results will be non-identifiable.

There will be no way to identify your data in any communication of results. The information collected as part of the study will be retained for 10 years and stored in the principal investigator’s office (University of Twente Drienerlolaan 5, Cubicus (building no. 41), room

B320, 7522 NB Enschede The Netherlands) and on secured electronic storage housed within the University of Twente, BMS Labs.

The researcher will take every care to remove responses from any identifying material as early as possible. Likewise individuals' responses will be kept confidential by the researcher and not be identified in the reporting of the research.

Summary report of this study's findings: When the study is published, a summary abstract of the findings will be made available to all participants. This summary will be sent via email as an electronic document upon request by the participant.

This project has been approved by the University of Twente BMS Ethics Committee. If you have any ethical concerns about the project or questions about your rights as a participant please contact the Secretary of this Committee:

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Appendix B

Consent Form for Dance-Step Motor Sequence Learning

You will be given a copy of this informed consent form.

Please tick the appropriate boxes	Yes	No
Taking part in the study		
I have read and understood the study information dated [__] (DD/MM/YYYY), or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	○	○
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	○	○
I understand that taking part in the study involves one laboratory session and data recording is performed on the computer with Xsens sensor technology.	○	○
Use of the information in the study		
I understand that information I provide will be used for publication, conference presentation and scientific reports.	○	○
I understand that personal information collected about me that can identify me, such as [e.g. my name or where I live], will be de-identified and not be shared beyond the study team.	○	○
Future use and reuse of the information by others		
I give permission for the *data* that I provide to be archived in BMS Datavault and made anonymous so it can be used for future research and learning.	○	○
I agree that my information may be shared with other researchers for future research studies that may be similar to this study or may be completely different. The information shared with other researchers will not include any	○	○

information that can directly identify me. Researchers will not contact me for additional permission to use this information.

I give the researchers permission to keep my contact information and to contact me for future research projects. ◯ ◯

Signatures

__________________________ ___________________ _______________

Name of participant [printed] Signature Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

__________________________ ___________________ _______________

Researcher name [printed] Signature Date

Study contact details for further information: Dr. Russell Chan, *r.w.chan@utwente.nl*

Contact Information for Questions about Your Rights as a Research Participant If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee of the Faculty of Behavioural, Management and Social Sciences at the University of Twente by ethicscommittee-bms@utwente.nl

Appendix C

Python Syntaxt to Extract the Data from E-Prime Text Files

```
import pandas as pd
import os
import re

#Here you choose the folder with the txt.files you want to merge into an
excel file
directory = r"C:/Users/Emma/Documents/Uni/Thesis/Data dance"

def clean_data(original_df):
    # split up all elements in df into [variable, value] and collect data
    in a list
    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] ==
            '***LogFrameEnd***':
            indices.append(row)

    return indices

def get_data (initial_df):

    #the other two functions are called to clean the data first and get the
      indices 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","feedback.RT"
      ,"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': flag=False; break #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,cueOnse
               tTime,cueOnsetDelay)= tuple(["X"]*7)
                if part_list[e][1] == 'cueprocedure' or part_list[e][1] ==
                  'responsprocedure':
                    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":proc
            edure,"sub trial number":count,
            "feedback.ACC":feedbackACC,"feedback.CRESP":feedbackCRESP,"feed
            back.RESP":feedbackRESP,"feedback.RT":feedbackRT,"h":h,"cue.Ons
            etTime":cueOnsetTime,"cue.OnsetDelay":cueOnsetDelay}
            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 file


    #final dataframe of one file is returned
    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_P23678.xlsx",index= False)
```

Appendix D

Python Syntax to Arrange the Data

```
import pandas as pd

df = pd.read_excel (r"C:/Users/Emma/Documents/Uni/Thesis/Code and df
dance/df_P23678.xlsx")


#arrange data on trial level: average RT and overall accuracy

block_columns=["subject","session","trial","sub_trial","accuracy","RT","h"]
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"])
            RT = RT / 6
            if accuracy==6: accuracy=1
            else: accuracy=0

                data_dict={"subject":row["subject"],"session":row["session"
                ],"trial":trial,"sub_trial":sub_trial,"accuracy":accuracy,"
                RT":RT/1000,"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"]==2:
        subjects.append(1)
    elif r["subject"]==3:
        subjects.append(2)
    elif r["subject"]==6:
        subjects.append(3)
    elif r["subject"]==7:
        subjects.append(4)
    elif r["subject"]==8:
        subjects.append(5)
df_block["subject"]=subjects

df_block.to_excel(r"C:/Users/Emma/Documents/Uni/Thesis/Code and df
dance/df_triallevel_23678.xlsx",index= False)
```

Appendix E

R Syntax for Non-Linear Mixed Effects Model (Learning Curves)

```
library(tidyverse)
library(mascutils)
library(bayr)
library(brms)
library(ggthemes)

df <- readxl::read_excel("C:/Users/Emma/Documents/Uni/Thesis/Code and df
dance/df_triallevel_23678with_h_subject.xlsx")

df$subject<- as.factor(df$subject)
mycolors=c("#6b5f3c","#ccc627","#54ab8e","#587ed1","#b04366")


## FREE LEARNING CURVES ##

# Free learning curve 1
# per subject per sequence
df %>%
  ggplot(aes(x = repetition,
             y = RT,
             color=subject)) +
  geom_point() +
  geom_smooth(se = F) +
  facet_wrap(~subject_h, scales = "free_y")+
  ylab("RT (s)")+
  xlab("Repetition")+
  ylim(0,1.288)+
  theme_minimal()+
  scale_color_manual(values=mycolors)

# Free learning curve 2
# Individual learning curves over blocks/reps

df %>%
  ggplot(aes(x = repetition,
             y = RT,
             group = subject,
             color=subject)) +
  geom_smooth(se = F)+
  scale_x_continuous(limits = c(0,192), expand = c(0, 0))+
  theme_classic()+
  ylab("RT (s)")+
  xlab("Repetition")+
  scale_color_manual(values=mycolors)+
  geom_vline(xintercept = c(24,48,72,96,120,144,168),colour="grey”,
show.legend=TRUE)+
  geom_text(aes(x=12, label="Block 1", y=0.1), colour="grey") +
  geom_text(aes(x=36, label="Block 2", y=0.1), colour="grey") +
  geom_text(aes(x=60, label="Block 3", y=0.1), colour="grey") +
  geom_text(aes(x=84, label="Block 4", y=0.1), colour="grey") +
  geom_text(aes(x=108, label="Block 5", y=0.1), colour="grey") +
  geom_text(aes(x=132, label="Block 6", y=0.1), colour="grey") +
  geom_text(aes(x=156, label="Block 7", y=0.1), colour="grey") +
  geom_text(aes(x=180, label="Block 8", y=0.1), colour="grey")

## NON-LINEAR MULTILEVEL REGRESSION ##

# specify formula, variables and weakly informative priors
F_ary <- formula(RT ~ asym + ampl * exp(-rate * repetition))
```

```
F_ary_ef_1 <- list(formula(ampl ~ 1|subject),
                   formula(rate ~ 1|subject),
                   formula(asym ~ 1|subject))

F_ary_prior <- c(set_prior("normal(5, 100)", nlpar = "ampl", lb = 0),
                 set_prior("normal(.5, 3)", nlpar = "rate", lb = 0),
                 set_prior("normal(3, 20)", nlpar = "asym", lb = 0))

# create model including MCMC sampling
M_1 <-
  df %>%
  brm(bf(F_ary,
         flist = F_ary_ef_1,
         nl = T),
      prior = F_ary_prior,
      family = "exgaussian",
      data = .,
      iter = 10,
      warmup = 8,
      save_pars=save_pars("subject"))

P_1 <- posterior(M_1)
PP_1 <- post_pred(M_1, thin = 10)

# save model estimates
save(M_1, P_1, PP_1, df, file = "model_estimates.Rda")

# get parameters for fixed effects, random factor variation and random
effects
bayr::fixef(P_1)
bayr::grpef(P_1)
P_1 %>% re_scores() %>% bayr::ranef()

## LEARNING CURVES BASED ON MODEL ESTIMATES ##
df$Subject<-df$subject
# learning curves per participant
df %>%
  mutate(M_1 = predict(PP_1)$center) %>%
  ggplot(aes(x = repetition,
             y = M_1,
             color=Subject)) +
  facet_wrap(~subject, scales = "free_y") +
  geom_smooth(se = F) +
  geom_point(alpha=0.2, size=1)+
  ylim(0,1.5)+
  labs(x="Trial",y="Model estimates")+
  theme_hc()+
  scale_color_manual(values=mycolors)

# crossbar plots for each parameter and participant
P_1 %>%
  re_scores() %>%
  bayr::ranef() %>%
  ggplot(aes(x = re_entity,
             y = center,
             ymin = lower,
             ymax = upper)) +
  facet_grid(nonlin~1, scales = "free_y") +
  geom_crossbar(width = .2) +
  labs(x = "Subject", y = "Model estimates") +
  theme_hc()
```

Appendix F

R Syntax for Linear Mixed Effects Model and Post-Hoc Tukey Test

```
library(lme4)
library(car)
library(effects)
library(tidyverse)
library(lsmeans)
library(ggthemes)

df <- readxl::read_excel("C:/Users/Emma/Documents/Uni/Thesis/Code and df
dance/df_keypresslevel2.xlsx")

#Creating factors
df$subject <- factor(df$subject)
df$Block <- factor(df$session)
df$key <- factor(df$key)
df$accuracy <- factor(df$accuracy)

m.footstep1 <- lmer(RT ~ key * Block + (accuracy|subject), data = df)
Anova(m.footstep1)

summary(m.footstep1)

##M1
#Need Effects lib
ae.m.footstep1<-allEffects(m.footstep1)
ae.m.df.footstep1<-as.data.frame(ae.m.footstep1[[1]])

#The main plot
ae.position<-ggplot(ae.m.df.footstep1, aes(x=key,y=fit, group=Block))+
  geom_ribbon(aes(ymin=lower, ymax=upper, fill=Block), alpha=0.2) +
  geom_line(aes(size=0.5, color=Block)) +
  geom_point(aes(color=Block, size=2))+
  ylab("RT (s)")+
  xlab("Position")+
  theme_classic()

#Printing Session effects facet
print(ae.position)

#Interaction post-hocs (Fifth model)
lsmeans(m.footstep1, pairwise ~ Block | key)

lsmeans(m.footstep1, pairwise ~ key | Block)
```

Appendix G

RT Contrasts between Key Positions for each Block

```
## $contrasts
## Block = 1:
##  contrast estimate     SE  df z.ratio p.value
##  1 - 2     0.18072 0.0494 Inf  3.661  0.0034
##  1 - 3     0.21624 0.0494 Inf  4.381  0.0002
##  1 - 4     0.26809 0.0494 Inf  5.425  <.0001
##  1 - 5     0.05984 0.0494 Inf  1.212  0.8314
##  1 - 6    -0.22044 0.0494 Inf -4.464  0.0001
##  2 - 3     0.03552 0.0494 Inf  0.720  0.9796
##  2 - 4     0.08737 0.0494 Inf  1.769  0.4859
##  2 - 5    -0.12088 0.0494 Inf -2.449  0.1397
##  2 - 6    -0.40116 0.0494 Inf -8.121  <.0001
##  3 - 4     0.05184 0.0494 Inf  1.050  0.9010
##  3 - 5    -0.15640 0.0494 Inf -3.169  0.0191
##  3 - 6    -0.43668 0.0494 Inf -8.840  <.0001
##  4 - 5    -0.20825 0.0494 Inf -4.218  0.0004
##  4 - 6    -0.48853 0.0494 Inf -9.890  <.0001
##  5 - 6    -0.28028 0.0494 Inf -5.673  <.0001
##
## Block = 2:
##  contrast estimate     SE  df z.ratio p.value
##  1 - 2     0.22649 0.0493 Inf  4.590  0.0001
##  1 - 3     0.27550 0.0494 Inf  5.582  <.0001
##  1 - 4     0.34441 0.0494 Inf  6.975  <.0001
##  1 - 5     0.29322 0.0494 Inf  5.939  <.0001
##  1 - 6     0.18485 0.0494 Inf  3.746  0.0025
##  2 - 3     0.04900 0.0494 Inf  0.993  0.9204
##  2 - 4     0.11791 0.0494 Inf  2.388  0.1602
##  2 - 5     0.06672 0.0494 Inf  1.352  0.7559
##  2 - 6    -0.04164 0.0494 Inf -0.844  0.9593
##  3 - 4     0.06891 0.0494 Inf  1.396  0.7294
##  3 - 5     0.01772 0.0494 Inf  0.359  0.9992
##  3 - 6    -0.09064 0.0494 Inf -1.836  0.4422
##  4 - 5    -0.05119 0.0493 Inf -1.037  0.9054
##  4 - 6    -0.15955 0.0494 Inf -3.231  0.0156
##  5 - 6    -0.10836 0.0494 Inf -2.195  0.2401
##
## Block = 3:
##  contrast estimate     SE  df z.ratio p.value
##  1 - 2     0.15736 0.0494 Inf  3.189  0.0179
##  1 - 3     0.21631 0.0494 Inf  4.382  0.0002
##  1 - 4     0.27171 0.0494 Inf  5.504  <.0001
##  1 - 5     0.19044 0.0494 Inf  3.857  0.0016
##  1 - 6     0.08367 0.0493 Inf  1.696  0.5347
##  2 - 3     0.05895 0.0493 Inf  1.195  0.8397
##  2 - 4     0.11435 0.0494 Inf  2.317  0.1871
##  2 - 5     0.03308 0.0494 Inf  0.670  0.9852
##  2 - 6    -0.07368 0.0494 Inf -1.493  0.6688
##  3 - 4     0.05540 0.0494 Inf  1.123  0.8722
##  3 - 5    -0.02587 0.0494 Inf -0.524  0.9952
##  3 - 6    -0.13263 0.0494 Inf -2.687  0.0777
##  4 - 5    -0.08128 0.0493 Inf -1.647  0.5671
##  4 - 6    -0.18804 0.0494 Inf -3.808  0.0019
##  5 - 6    -0.10676 0.0494 Inf -2.162  0.2556
##
## Block = 4:
##  contrast estimate     SE  df z.ratio p.value
##  1 - 2     0.15081 0.0493 Inf  3.056  0.0272
##  1 - 3     0.19532 0.0493 Inf  3.958  0.0011
```

```
##  1 - 4     0.23851 0.0494 Inf  4.833  <.0001
##  1 - 5     0.16192 0.0494 Inf  3.281  0.0133
##  1 - 6     0.09788 0.0493 Inf  1.983  0.3518
##  2 - 3     0.04451 0.0493 Inf  0.902  0.9461
##  2 - 4     0.08770 0.0494 Inf  1.777  0.4807
##  2 - 5     0.01111 0.0494 Inf  0.225  0.9999
##  2 - 6    -0.05293 0.0493 Inf -1.073  0.8924
##  3 - 4     0.04319 0.0493 Inf  0.875  0.9525
##  3 - 5    -0.03340 0.0494 Inf -0.677  0.9845
##  3 - 6    -0.09744 0.0493 Inf -1.975  0.3570
##  4 - 5    -0.07659 0.0493 Inf -1.552  0.6304
##  4 - 6    -0.14064 0.0494 Inf -2.849  0.0500
##  5 - 6    -0.06405 0.0494 Inf -1.298  0.7865
##
## Block = 5:
##  contrast estimate     SE  df z.ratio p.value
##  1 - 2     0.19971 0.0494 Inf  4.047  0.0007
##  1 - 3     0.21573 0.0494 Inf  4.371  0.0002
##  1 - 4     0.25481 0.0494 Inf  5.162  <.0001
##  1 - 5     0.18316 0.0494 Inf  3.711  0.0028
##  1 - 6     0.11282 0.0493 Inf  2.286  0.1995
##  2 - 3     0.01603 0.0493 Inf  0.325  0.9995
##  2 - 4     0.05510 0.0493 Inf  1.117  0.8747
##  2 - 5    -0.01655 0.0493 Inf -0.335  0.9994
##  2 - 6    -0.08689 0.0494 Inf -1.761  0.4915
##  3 - 4     0.03907 0.0493 Inf  0.792  0.9690
##  3 - 5    -0.03258 0.0493 Inf -0.660  0.9862
##  3 - 6    -0.10292 0.0494 Inf -2.085  0.2950
##  4 - 5    -0.07165 0.0493 Inf -1.452  0.6950
##  4 - 6    -0.14199 0.0494 Inf -2.877  0.0463
##  5 - 6    -0.07034 0.0494 Inf -1.425  0.7116
##
## Block = 6:
##  contrast estimate     SE  df z.ratio p.value
##  1 - 2     0.20755 0.0493 Inf  4.206  0.0004
##  1 - 3     0.23913 0.0494 Inf  4.845  <.0001
##  1 - 4     0.27319 0.0494 Inf  5.534  <.0001
##  1 - 5     0.22262 0.0494 Inf  4.510  0.0001
##  1 - 6     0.09634 0.0493 Inf  1.952  0.3702
##  2 - 3     0.03159 0.0493 Inf  0.640  0.9880
##  2 - 4     0.06564 0.0494 Inf  1.330  0.7684
##  2 - 5     0.01507 0.0494 Inf  0.305  0.9996
##  2 - 6    -0.11121 0.0494 Inf -2.253  0.2135
##  3 - 4     0.03406 0.0493 Inf  0.690  0.9831
##  3 - 5    -0.01651 0.0493 Inf -0.335  0.9994
##  3 - 6    -0.14279 0.0494 Inf -2.893  0.0442
##  4 - 5    -0.05057 0.0493 Inf -1.025  0.9098
##  4 - 6    -0.17685 0.0494 Inf -3.582  0.0046
##  5 - 6    -0.12628 0.0494 Inf -2.558  0.1079
##
## Block = 7:
##  contrast estimate     SE  df z.ratio p.value
##  1 - 2     0.14081 0.0494 Inf  2.853  0.0495
##  1 - 3     0.17808 0.0494 Inf  3.608  0.0042
##  1 - 4     0.21209 0.0494 Inf  4.297  0.0003
##  1 - 5     0.14676 0.0494 Inf  2.973  0.0350
##  1 - 6     0.07655 0.0494 Inf  1.551  0.6310
##  2 - 3     0.03728 0.0493 Inf  0.755  0.9747
##  2 - 4     0.07129 0.0493 Inf  1.445  0.6996
##  2 - 5     0.00596 0.0494 Inf  0.121  1.0000
##  2 - 6    -0.06425 0.0494 Inf -1.302  0.7844
##  3 - 4     0.03401 0.0493 Inf  0.689  0.9832
##  3 - 5    -0.03132 0.0493 Inf -0.635  0.9884
```

```
##  3 - 6    -0.10153 0.0494 Inf -2.056  0.3106
##  4 - 5    -0.06533 0.0493 Inf -1.324  0.7719
##  4 - 6    -0.13554 0.0494 Inf -2.745  0.0667
##  5 - 6    -0.07021 0.0494 Inf -1.422  0.7137
##
## Block = 8:
##  contrast estimate     SE  df z.ratio p.value
##  1 - 2     0.08102 0.0494 Inf  1.642  0.5707
##  1 - 3     0.12011 0.0494 Inf  2.433  0.1447
##  1 - 4     0.16542 0.0494 Inf  3.351  0.0104
##  1 - 5     0.09124 0.0494 Inf  1.848  0.4346
##  1 - 6    -0.00296 0.0494 Inf -0.060  1.0000
##  2 - 3     0.03909 0.0493 Inf  0.792  0.9690
##  2 - 4     0.08440 0.0493 Inf  1.710  0.5249
##  2 - 5     0.01022 0.0493 Inf  0.207  0.9999
##  2 - 6    -0.08398 0.0494 Inf -1.701  0.5310
##  3 - 4     0.04531 0.0493 Inf  0.918  0.9420
##  3 - 5    -0.02887 0.0493 Inf -0.585  0.9920
##  3 - 6    -0.12306 0.0494 Inf -2.493  0.1262
##  4 - 5    -0.07418 0.0493 Inf -1.503  0.6622
##  4 - 6    -0.16837 0.0494 Inf -3.410  0.0085
##  5 - 6    -0.09419 0.0494 Inf -1.907  0.3976
##
## Degrees-of-freedom method: asymptotic
## P value adjustment: tukey method for comparing a family of 6 estimates
```