Motor learning performance differences in simulated flexible bronchoscopies

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Abstract

Motor sequence learning (MSL) has been a staple in psychological research for as long as it has been discovered. One area that relies heavily on efficiency regarding skills rooted in the theory of MSL are Minimally Invasive Surgeries (MIS). A prominent MIS performed regularly are flexible bronchoscopies. Therefore this thesis focuses on assessing the individual differences and learning potentials in a simulated flexible bronchoscopy setting, based on the theory of learning curves, established by Hearhcote et al. (2000). Ten novices (7 females; $M(age) = 20.1$; $SD(age) = 2.51$) in the field of bronchoscopy were recruited through the University of Twente SONA student system to take part in the experiment, requiring them to perform flexible bronchoscopies on the GI-BRONCH Mentor™ while wearing an Xsens MVN Awinda motion capture suit collecting data on their acceleration potential. All of the subjects showed improvement during both of the Tasks assessed in this experiment. Learning curves on the movement time per participant, as well as acceleration potential show ambiguous results. There is also no clear transferability of skills between tasks within the results, as indicated in the learning curve parameters. The measured acceleration potential did not have direct influence on success during this experiment. However, consistency of the measured tasks was found to be a possible factor in the lack of clear results. Small trial size, as well as varying difficulty within Task 1 are both potential influences that would ideally be revised in future research. Conclusively, while the results of this experiment showed improvement within subjects, as well as giving indications on individual differences, no clear statements about learning curve parameter potential can be made.

1.0 Introduction

Motor sequence learning (MSL) has been a staple in psychological research for as long as it has been discovered. Not only does MSL spark scientific research on the underlying psychological processes involved in motor skill acquisition, but nearly every person engages in some form of MSL in most daily activities. Be it getting dressed in the morning or cooking ones' favourite meal for dinner, all physical activities are built upon MSL. In general, MSL tries to conceptualise the efficiency, precision, and speed, at which a person acquires a new sequence of movements (Abrahamse et al., 2013). When a new sequence has been learned, the reproduction of said sequence is empirically more efficient, while less cognitive effort is required. There has been research on MSL, specifically on the differences between externally and internally guided performance of motor sequences. While externally guided control relies on external cues and assistance, internally guided control builds upon a well-established internalised representation, which enables motor sequence production at a rapid pace. (Verwey & Abrahamse, 2012). However, up until recent years, research on the topic of MSL in general has been limited by the technology available. With more accurate research tools emerging rapidly in many sectors, studies on MSL are now becoming increasingly sophisticated with new interest. Keeping aside aspects important to skill acquisition like decision making and perspective taking, the action movement of certain areas related to a specific task might allow for more accurate theories with said technology (Verstynen et al., 2012).

1.1 Technology in research and education

In many cases, research on the validity of new technologies like training simulators and virtual reality (VR) applications in practice is highly explorative. Given the industry revolving around this technology was primarily driven by the entertainment sector, namely gaming and special effect filmmaking, research results on the educational benefit of these appliances are scarce. However, with recent developments embracing the research sector, the progress in research tools may allow for new ways of empirically assessing their usefulness in whole new ways (Paré & Joordens, 2009). When considering skills on the basis of MSL, researchers might be interested in the differences of miniscule movements of certain areas when participants perform a specific task. In order to do so, researchers have started to rely more on motion tracking technology. With current motion tracking, researchers are able to accurately simulate and record movements of a subject, often providing useful data on positioning, velocity or inertia (van Schaik & Dominici, 2020). With said data, new insights

on applied research fields can be enhanced. Furthermore, existing theories might be reconceptualized, as more accurate statements regarding individual processes can be empirically made (Sandbank & Cascio, 2019).

Not only theoretical constructs within the field of Psychology may benefit from this variety of insights into the topic (of applied functions), but also applications and education in common professions could enjoy a plethora of new possibilities. Since an overwhelming majority of professions in our current time build upon experience and execution of motor sequences with high precision and efficiency, these areas might very well benefit from a deeper understanding of MSL (Du & Clark, 2017). One major area is the medical sector. The benefits of optimising the acquisition of motor skills within this sector, especially, are promising. Medical students acquiring and learning complex movements more efficiently might reduce patient risk or other complications of less precise movements during procedures (Michael et al., 2014). A lot of medical practice appliances already use advanced technology like surgical skill evaluation during simulator training or VR simulator surgical skills education. Research on the advantages of such methods show generally optimistic results with some showing significant improvements (Khoo et al., 2021). Nonetheless, simulator training poses no risks for actual patients in all cases, as they are entirely absent from the virtual education process.

1.2 Minimally invasive surgery (MIS)

A prominent candidate within the medical curriculum for training with technology is minimally invasive surgery (MIS). Over the last decade, the number of MIS performed has rapidly increased (Tsui, Klein & Garabrant, 2013). In general, MIS are procedures, which offer a variety of advantages over open surgery. Namely, less blood loss, reduced sensation of pain and shorter hospital stays for patients (Pache et al., 2017). Nonetheless, compared to traditional open surgery, MIS requires the surgeon to master highly complex skills involving interpreting 3D information within 2D images, general lack of haptic feedback during the procedure, as well as high efficacy regarding visual-spatial ability and psychomotor skills (Gallagher, Leonard & Traynor, 2009). These factors affect the learning abilities of MIS in general greatly, often prolonging training duration compared to traditional surgeries, due to an initial lack of competency within the practising surgeon during training (Fuchs, 2002). The success rate of acquiring the skill of a MIS varies, with some learners showing high potential very early into the training, while some learners are expected to never reach proficiency at all (Grantcharov & Funch-Jensen, 2009). While extensive individual training might eventually

help surgeons of the latter group achieve a basic adequacy in selected MIS, the more common approach consists of providing the recommendation of considering to pursue a different career, therefore failure rate for MIS is considered generally high (Hofstad et al., 2013). Moreover, the training conditions around teaching MIS are considered less than optimal, regarding educational theories. Not only are the general tools of selection for a successful MIS less than scientific, but they also rely greatly on individual opinion and are prone to biases of the instructor. Resulting from these shortcomings, MIS instruction and training is widely criticised within the medical community, due to lack of objectivity (Fielding, Maldonado & Murgu, 2014). Moreover, individual differences are widely unaccounted for, within the educational process, as well as in the area of MIS itself (Wahidi et al., 2010).

1.3 The current state of bronchoscopy

One type of MIS administered regularly are bronchoscopies. During a bronchoscopy, physicians must conduct visual inspections by inserting the bronchoscope into the patients' airways through their mouth or nose. While within the patient, a bronchoscope further enables the physician to take biopsies or administer injections, as well as extraction of foreign entities, all while offering advantages like reduced time of the procedure and minimal risk of complications for the patient (Wang et al., 2020). There have been prominent changes in the administration and procedure of bronchoscopies since its initial invention. The most prevalent change in the history of bronchoscopies is the introduction of the flexible bronchoscope by thoracic surgeon Shigeto Ikeda in the 1960s. Prior to Dr. Ikeda's idea of implementing fibre optic bundles and a movable distal tip allowing for angulation, medical professionals were bound to rely on rigid bronchoscopies, in which entry to the airways was given through a metal pipe (Miller et al., 2018). With this revolutionary new form of bronchoscopy, as well as technology in general becoming more and more sophisticated, training methods gradually shifted towards implementing simulations. By relying on simulators, rather than practising on live patients, patient risk of being harmed by inept malpractice during training is eliminated, given no patient is involved with the early process of acquiring the skills. Those risks, although very unlikely, have proven to be fatal in the past, making the concept of simulation much more attractive for the medical community (Stahl et al., 2015). Nonetheless, the training associated to the skills necessary for flexible bronchoscopies are difficult for new medical professionals to learn as it poses a challenge to interpret the 2D information on screen, relating to the 3D environment of the body, as well as being generally challenging in terms of dexterity (Nilsson et al., 2017). Since simulators not only allow for more standardised training processes but also enable access to new dimensions of data and research possibilities, new

insights on the skill of bronchoscopy could be gained. Fundamentally, assessing the differences in body positioning between groups with distinct, differing professionality regarding the skill, could allow for new explanations on the learning process of bronchoscopies.

Currently, pulmonology trainees are educated in different ways, depending on the institution providing the education. This varying assortment of assessment criteria has multiple disadvantages compared to a standardised training program (Voduc et al., 2020). Common problems of education like biases of the educator, lack of reliable scoring or assignments with unsupported validity are amplified by the lack of a standardised curriculum. In response to this issue, many institutions already rely on simulator training equipped with bronchoscopy curriculums like CHEST (Eickelmann, Waldner & Huwendiek, 2021). With the assistance of these simulators, instructors are able to create more accurate reflections of the trainees progress and competence. A prominent way to track a learner on these dimensions is deriving a learning curve from the assessment data. With learning curves, instructors have the possibility to track and, more significantly, predict individual learning progress (Voduc et al., 2020). With this information it is possible to better instruct each individual pulmonology student based on their needs.

1.4 This experiment

Taking all that has been mentioned into account, this thesis will concern itself with the individual differences and potential learning effects between participants within a simulated flexible bronchoscopy situation. The first prediction is that all individuals will exhibit some form of improvement over the course of the experiment, showcasing a reduction in movement time per trial across the tasks. I also predict that a relationship between free sensor-acceleration on the cartesian x-axis and successful bronchoscopies in thatless acceleration may contribute to well performed trials.

2.0 Methods

2.1 Design

The study makes use of a between-subject design, given the individual differences is the main dimension of interest. Aggregated data is utilised to showcase learning effects across the different tasks. This study is part of a large-scale research effort aimed at assessing the differences between not only subjects, but also subject-groups, all subject to multiple different

projects that are performed in stages. This experiment was approved by the University of Twente Ethics committee in the Netherlands.

2.2 Participants

Ten participants (7 females; M(age) = 20.1; SD(age) = 2.51), mostly recruited through the University of Twente SONA system which grants students credits for their voluntary participation in student studies, took part in the experiment. Additionally, another participant available in the near proximity (<20km) was recruited through the acquaintanceship of the researcher. All participants were students, with nine of the ten being enrolled at the University of Twente, and one at the Saxion University of Applied Sciences. Three of the participants stated to be of Dutch nationality, five of German nationality, and two of other nationalities. Given the handedness of the participants influenced the data analysis, it was asked prior to the experiment. Two of the participants were left-handed, while eight participants were right-handed. As a special request, in order to ensure a correct fit of the motion sensor gear, all participants were asked to wear tight fitting clothing, to which all complied. No unique conditions interfering with the study setup were recorded.

2.3 GI-BRONCH Mentor™

All tasks were performed on the GI-BRONCH Mentor™ virtual reality simulator, developed by 3D Systems (previously Simbionix), Cleveland, OH, USA. It was developed to be used as a bronchoscopy training tool, offering a variety of simulations for a multitude of clinical bronchoscopy procedures. (Simbionix, 2018b) The simulator itself is equipped with bronchoscopy tools like an aspirating needle, biopsy forceps and cytology brush. Mouth and nose entrances for bronchoscopies and upper endoscopies come in the form of plastic mannequin faces, one facing upwards, one facing 90° to the left, enabling numerous different simulations. The simulator's authentic bronchoscope includes Pentax ECS-3804F tactile feedback and a movement sensor at the tip of the scope, allowing for a computer-generated dynamic endoscopic view. To display the simulation environment the simulator makes use of a display consisting of a 24-inch LCD touch screen.

Figure 1. GI-BRONCH Mentor™ by 3D Systems (fka.: Simbionix).

A total of four modules, each including various scenarios with alternating complexity are available with the GI-BRONCH Mentor™. Those modules, namely Essential Bronchoscopy, Emergency Bronchoscopy, CHEST Standardised Curriculum and Essential EBUS, rely on the bronchoscopy training curriculum and aims to test the users' anatomical skills empirically. The tasks relevant for this study are Task 1 and Task 3.

Task 1, required the participant to follow a blue ball through the virtual environment of a metal tube. While doing so, the ball would, depending on the randomly selected version of Task 1, choose different paths, allowing for an assessment of the general dexterity of the participant with a bronchoscope. While trying to manoeuvre through the course, the participants' contact with the wall, indicated by a shattering sound, was measured, with as little contact as possible being the most desirable outcome. Other measured dimensions include the time of completion and an overall score for the performance of the participant in that particular trial. The duration of this task was set to be under 3 minutes in most of the

cases.

Figure 2. Essential Bronchoscopy: Task 1

Task 3, presented the participants with a more realistic virtual environment of a human airway system. Contrary to Task 1, there was no ball or other guidance to follow visually by the participant. Instead, the goal of Task 3 was to find and confirm 18 different points within the human airway system, which was achieved by successfully entering the desired pathway and hovering over the displayed "?"- icon within the virtual environment, until said icon lit up with green colour. This task did not require the participant to know and remember which segments are located in what part of the airway system, nor how to reach them. Similar to Task 1, this task was also aimed at solely assessing the participants dexterity with a bronchoscope. Therefore, the researchers guided the participant verbally on where to reach the next segment.

In comparison to Task 1, Task 3 required frequent retracting of the scope, which occasionally required further guidance from the researchers. After progressing through both halves and checking all icons, the participant has completed the task. It is important to note that during this task, the participant was not visually rewarded by a winning screen, but was instead notified by the researcher present that the task was completed.

Figure 3. Essential Bronchoscopy: Task 3.

2.4 Motion capture technology: Xsens

In order to obtain meaningful results on the competence of participants, the Xsens MVN Awinda motion capture setup was used (Xsens, 2017). For this study, 17 sensors were attached to the participants body, six sensors on the lower body and 11 on the upper body, attached by velcro tape and a specially designed t-shirt, respectively. The sensors were located on both hands, both forearms, both upper arms, both shoulders, the sternum, the pelvis, the head, both upper legs, both lower legs and both feet. Additionally another sensor has been attached to the bronchoscope of the simulator, therefore using the complete 17(+1) full-body setup (Xsens, 2017). During the experiment, data on the free-sensor acceleration and positioning was sent to the Awinda station, which in turn supplied the main workstation through MVN Analyze with an accurate recording. Data extraction was performed with the help of MVN Analyze as well.

Figure 4. Xsens full-body motion suit setup (incl. sensor placement)

2.5 Procedure

After welcoming the participant, the researcher briefed them on the purpose of the experiment and informed them that withdrawal is possible at any time without further consequences. Then, the participant was asked to read and sign the consent form, followed by the answering of all questions the participant might have had. The participant was then fitted with the Xsens motion capture gear comfortably. After the sensors were put in place, the participant was asked to perform the calibration procedure, guided by the researchers. For that, the participant was advised to stand in a comfortable position on a predetermined calibration spot, walking a four-metre line in a relaxed manner, turning around and walking back to the starting point, again being asked to turn around 180 degrees and standing in the starting position once more. This was repeated until an acceptable calibration was achieved. Then, the participant was asked to take their position in front of the simulator. There, the researcher explained the bronchoscope to the participant, advising them on how to use it in its most basic form. After understanding how to operate the bronchoscope, the actual testing commenced. For that, first the participant was asked to perform Task 1 five times, with the beginning and end of each trial being announced by the researcher situated next to the participant. When the participants completed all five trials of Task 1, they were then offered a short break of 10 minutes, during which the researcher explained the next task. After the

break, the participant was shown a complete demonstration of Task 3 by the researcher. As soon as the participant signalled to be ready, they were asked to perform the task they were just shown three times on their own, being offered a short 2-3 minute break after each trial. Again, the start and end of each trial was announced by the researcher next to the participant. When finishing the third and final trial, the participant was helped out of the motion capture gear and debriefed. Finally the participant was thanked for their participation and excused.

2.6 Data analysis

Prior to the analysis of the data, data extraction was performed by converting the resulting .mvnx file into an Excel (.xlsx) file. The next step was creating a usable dataset with relevant information on a participants movement time in seconds (calculated by dividing the time spent on one trial by the number of hertz recorded within the data set, in all cases equalling 30) for each task, named behavioural data. In two additional files, the free acceleration of the wrist and prop sensors were collected. Given the sheer amount of data available with a Xsens full-body setup, the data corresponding to the wrists and prop were identified and collected in a separate Excel file, then combined into a data set for analysis. As for the data of the three sensors, another column listing the data with only a participants' dominant hand movement on the cartesian X-axis was created. The now extracted four data sets were then converted into a .csv file for analysis in R-Studio (Version 4.1.2.). The first analysis that was run was a linear mixed effect model on the behavioural data for each separate task. The variables 'Participant' and 'Trial' were used as factors, with 'Trial' being an ordered factor. A maximum likelihood estimation was used, to allow for comparison between multiple trials. After running post-hoc analysis through the emmeans package, providing information like estimated marginal means and comparisons thereof, one effect plot for each of the conditions was created with the x-axis displaying the trial and the y-axis representing the recorded movement time in seconds across the whole sample.

In the next step of analysis, the behavioural data was analysed in the context of free learning curves. Learning curves offer information about a learners' progress and performance based on three parameters: Amplitude, Asymptote and Rate. The Amplitude provides information on the improvement of the subject, the Asymptote estimates the maximum performance of an individual, and the Rate visualises the speed at which the participant improved. Considering the parameters for this thesis, namely movement time per trial, Hearhcote et al. (2000) provided the formula for creating the model as follows:

(1) $ypN = Asymp + Amplp \cdot exp(-Ratep \cdot N)$

y: movement time

p: participant

N: trial

Figure 5. Learning curve parameters (Wiechmann, 2021).

For this thesis, the Asymptote parameter offers the least valuable information, as it can be misleading, should a subject start off with an initially high score, and keep that score consistently, hence not showing much improvement over the course of a task. However, the parameters Amplitude and Rate are especially interesting for this research, as they can offer valuable visualisation for potential individual differences in initial performance, as well as improvement within the tasks. Additionally, it is a useful indicator for potential transferability of skills, as a high Amplitude parameter in Task 3 would indicate that certain skills required for bronchoscopies have been acquired during Task 1. Naturally, still all three parameters are included within the analysis, in order to understand different representations of individual learning progress. The tasks were analysed separately, for behavioural changes within task. It is important to notice that the independent variable used in this case does not correspond to the number of trials, but the number of repetitions of the task in question. The Movement Time in seconds (MT (s)) is still analysed as the dependent variable. Furthermore, an ex-gaussian distribution was fitted to the MT in order to approximate a posterior distribution

using Markov-Chain Monte Carlo sampling. Finally, a crossbar plot was constructed to visualise each parameter for each subject.

The two remaining data sets, both including the Xsens acceleration data for each task respectively, were also analysed with free learning curves. In this case, the x-axis was set as the recorded timeframes for a trial, while the y-axis was coded to be the free acceleration data for the dominant hand of the participant. To segregate the trials from other adjustments to the variables were made. Firstly, the x-axis, previously the raw time for each trial, was manipulated to account for the individual differences in finishing times and at the same time account for repetitions of practice. For Task 1, the recorded time of each participant was added by 10,000 for trial 2, 20,000 for trial 3, et cetera. For Task 3, the same was executed, but instead adding 20,000 for trial 2 and 40,000 for trial 3. This new time parameter accounts for the repetitions of trials and was used for subsequent analysis. After creating the learning curves for each participant over trials as before, another two posterior distributions using Markov-Chain Monte Carlo sampling were created. With the resulting data, tables with the coefficient estimates of all participants on each parameter have been computed. Lastly, for visualisation, crossbar plots based on the model estimates per subject were constructed.

3.0 Results

3.1 Raw data

In order to get a broad overview of how well the participants did, and whether or not there is learning occurred, the raw data was first investigated. For that, the MT(s) was illustrated by the number of repetitions of the task in question. Therefore, for Task 1 repetitions started at 0 (new performance) and ended at 4 (= 5 practises), implying that for Task 3 repetitions ended at 2. Therefore my observation of the raw data is, that a majority of the participants show a learning effect for Task 1, while all of them exhibited one for Task 3.

Figure 6. Visualisation of Task 1 movement time performance. Each subject was assigned a different colour, while also being identified by their number above each illustration. Rep represents the number of repetitions of practice while MT(s) shows the movement time in seconds (mean= 102.23, sd= 55.49). Apart from subject 1 and 5, all displayed an overall learning effect, while everybody except subject 5 displayed some improvement within the first repetition.

Figure 7. Visualisation of Task 3 movement time performance. Again, Rep represents the number of repetitions while MT(s) shows the movement time in seconds (mean= 533.53, sd= 143.23). All of the subjects display an overall learning effect, except subject 9 all improved within the first repetition.

3.2 Linear mixed model

After getting a general idea of how each subject performed, the linear mixed models were performed to compare the overall differences between trials. For Task 1, the trials exhibit seemingly no significant effect X^2 (4, $N = 50$) = 29.11, $p = 7.43$. However, comparing the model estimates of each trial separately within Table 1, one can see the biggest improvement between trial 1 and 5, at a contrast of 83.09. Mainly, this big positive change seems to be happening between trial 1 and 2, showing a contrast of 72.35. What stands out is the fact that there seems to be a general deterioration of success in subject performance between trial 2 and 4, at a contrast of -13.36. It is important to mention that all p-values regarding the contrast between trial 1 and all following trials were significant, with the most probable positive change between trial 1 and 5 (p= 0.0003).

Table 1

Linear-mixed model: mean contrast trial comparison, Task 1.

Contrast	Estimate	SE	Df	T-ratio	P-value
1 - 2	72.35	17.9	44.4	4.042	0.0019
1 - 3	63.26	17.9	44.4	3.534	0.0082
1 - 4	58.99	17.9	44.4	3.295	0.0158
1 - 5	83.09	17.9	44.4	4.641	0.0003
2 - 3	-9.09	17.9	44.4	-0.508	0.9862
2 - 4	-13.36	17.9	44.4	-0.746	0.9443
2 - 5	10.74	17.9	44.4	0.600	0.9744
3 - 4	-4.26	17.9	44.4	-0.238	0.9993
3 - 5	19.83	17.9	44.4	1.108	0.8015
4 - 5	24.10	17.9	44.4	1.346	0.6644

Figure 8. Visualisation for Table 1. Each trials' mean movement time is displayed and compared. Main effect seems to be predicated through the difference between trial 1 and 2. Two negative changes (between trial 2 and 3, as well as 3 and 4 respectively) can be noticed. Overall improvement (trial 1 vs 5) is apparent within the graph.

Table 2 focuses on the same parameters within Task 3. As only three trials were recorded per subject, the comparison had only three instances. Similar to Task 1, no clear significant overall effect has been recorded X^2 (2, $N = 30$) = 40.36, p = 1.79. However, we observed a general improvement over each consecutive trial and the biggest change was observed when checking the overall improvement. Between trial 1 and 3, there has been a contrast of 165.1 (t= 5.9), made up by the positive change between trial 1 and 2 of 112.4 (t= 4.017), and supported by the slighter change between trial 2 and 3, of 52.7 (t= 1.882). Contrary to Task 1, there has not been, at any point during testing, an increase in movement time. When considering the p-values it seems there has been a significant effect between trial 1 and 2 (p= 0.0016) and between trial 1 and 3 (p= <0.0001). However, although at first glance showing improvement within the contrast, no significant p-value was found between trial 2 and 3 (p= 0.1672).

Table 2

Linear-mixed model: mean contrast trial comparison, Task 3.

Contrast	Estimate	SE	Df	T-ratio	P-value
1 - 2	112.4	28	22.2	4.017	0.0016
1 - 3	165.1	28	22.2	5.900	<.0001
2 - 3	52.7	28	22.2	1.882	0.1672

Figure 9. Visualisation for Table 2. Each trials' mean movement time is displayed and compared. Less apparent differences can be seen. Still, the main effect seems to again be predicated through the changes between trial 1 and 2. Unlike during Task 1, there is no negative change in movement time (s) during Task 3.

3.3 Learning curves

After inspecting the data in its raw form, as well as running linear mixed models on the data, learning curves were created for all four data sets. For the behavioural data, the previously obtained model estimation was run with the learning curve formula. The resulting output showed the three parameters of learning curves for each participant. As *Amplitude* is the parameter most significant for this thesis, subjects were mainly compared on this dimension. This is due to the fact that Amplitude can give an indication on the graveness of individual differences, as it shows us the initial starting potential for each subject in a comparable manner. For Task 1, the differences between subjects vary greatly. While subject 7 exhibits the greatest rate of improvement at 1.66, subject 5 shows the least improvement, at a rate of 0.443. However, the fluctuation of rates seems to be higher for other subjects, as subject 6 shows an upper limit learning rate of 8.535.

Figure 10. Crossbar plot for behavioural data showing learning curve parameters for Task 1. The Rate, Amplitude and Asymptote parameters for each subject are represented within. The bold black bar visualises the subjects median value for each parameter, while the upper and lower limits indicate more accurate centre estimates through the 95% confidence interval.

Figure 11. Visualisation modelled behavioural learning curves Task 1.

Regarding Task 3, differences in learning rate seemed to be slightly bigger than during Task 1. The biggest increase in improvement was recorded for subject 4 at a rate of 4.508, while subject 7 improved the least at a rate of 3.149. Again, the upper limit rate was achieved by a different subject, as subject 10 seemed to show an increase of 7.976 at times.

Figure 12. Crossbar plot for behavioural data showing learning curve parameters for Task 3. The Rate, Amplitude and Asymptote parameters for each subject are represented within. The bold black bar visualises the subjects median value for each parameter, while the upper and lower limits indicate more accurate centre estimates through the 95% confidence interval.

Figure 13. Visualisation behavioural learning curves Task 3.

3.4 Acceleration data

The acceleration data of the sensor on the hand for both tasks was analysed in the same manner as the behavioural data. First looking at the initial change of positioning of each subject during Task 1, one can notice that there are very significant differences in recorded sensor data. While some subjects barely altered their movement over the duration of the task, some did so very much, showing changes in either direction. Subject 1 and 8 both showed declining acceleration with similar rates during the experiment, subject 6 showed a rapid increase in acceleration. The remaining subjects did not exhibit changes across the task repetitions, although subject 3 and 9 did increase and decrease their acceleration slightly, respectively.

Figure 14. Visualisation of subjects' acceleration on a cartesian x-axis, regarding their dominant hand, Task 1. X-Axis shows the manipulated time for each trial, the Y-axis shows the acceleration potential of each subject. The time parameter has been altered by increasing it by 10000 each after the first repetition, in order to account for major discrepancies in finishing time. Individual differences between subjects seem to be very prominent. Changes, or the lack thereof, does stay consistent in either direction for each subject, over the course of the task.

For Task 3, one can see a similar result, although with an anomaly. While most subjects show no strong alteration in acceleration over the course of the task, subject 6 and 9 show different changes. Subject 9 exhibits a clear tendency to decrease acceleration, while subject 6 has massive deceleration within later trials.

Figure 15. Visualisation of subjects acceleration on a cartesian x-axis, regarding their dominant hand, Task 3. X-Axis shows the manipulated time for each trial, the Y-axis shows the acceleration potential of each subject. The time parameter has been altered by increasing it by 20000 each after the first repetition, in order to account for major discrepancies in finishing time. Similar to Task 1, subjects seem to differ in their acceleration, although during this task, a majority of subjects skewed towards moving less on the x-axis (towards 0.00). Subject 6 however seems to greatly change their acceleration potential within and between trials greatly.

Lastly, learning curves for both tasks of each subject were created. It is important to notice that differences between subjects in terms of their Amplitude and Asymptote estimations were very prominent in this output. During both tasks, subjects seem to differ greatly in all three parameters. However, during Task 1, the Rate at which subjects seemed to change their level of acceleration seems to be more consistent across subjects, than during Task 3.

Figure 16. Crossbar plot for acceleration data showing the learning curve parameters for Task 1. The Rate, Amplitude and Asymptote parameters for each subject are represented within. The bold black bar visualises the subjects median value for each parameter, while the upper and lower limits indicate more accurate centre estimates through the 95% confidence interval.

Figure 17. Visualisation acceleration learning curves Task 1. X-Axis shows the time of each trial, again manipulated by 10000 for each repetition. Y-Axis shows the model estimates for acceleration potential. Wider bars represent more time spent on a trial, taller bars represent a subject showing more acceleration potential during the trial.

Figure 18. Crossbar plot for acceleration data showing the learning curve parameters for Task 3. The Rate, Amplitude and Asymptote parameters for each subject are represented within. The bold black bar visualises the subjects median value for each parameter, while the upper and lower limits indicate more accurate centre estimates through the 95% confidence interval.

Figure 19. Visualisation acceleration learning curves Task 3. X-Axis shows the time of each trial, again manipulated by 20000 for each repetition. Y-Axis shows the model estimates for acceleration potential. Wider bars represent more time spent on a trial, taller bars represent a subject showing more acceleration potential during the trial. As a Task 3 trial generally took longer than a Task 1 trial, more varying potential of acceleration was recorded, therefore showing similar bar-height within the visualisation.

4.0 Discussion

This thesis aimed at quantifying the learning effects occurring within subjects while performing a simulated flexible bronchoscopy, as well as assessing the individual difference prominent between individual subjects. In order to do so, the participating subjects' behavioural data, in this case movement time per trial, as well as their free acceleration on cartesian coordinates, realised by Xsens motion capture technology, was assessed with a between-subject study design. Subsequent to the very successful data collection, made possible by the hard work of all the collaborating professionals, thorough analysis of the resulting data, both the behavioural data, but especially the acceleration data yield ambiguous results.

Firstly, it is important to mention that subjects seemed to differ in terms of their initial skills greatly. For example, when comparing the first trial of Task 1 of the fastest-performing subject, Subject 1, and the slowest-performing subject, Subject 10, a difference of 172.86 seconds of movement time was observed. This immense difference does not seem to subside with the last trial, as Subject 7, the fastest during trial 5, still required 148.34 seconds less movement time than Subject 5, the slowest performing one.These significant incoherencies could be solely accounted to individual differences, although the path which was randomly chosen for Task 1 each trial might have had an influence on that. Surprisingly, the learning curve parameters for Task 1 barely reflect these rather great differences. If we compare Subject 7, which is considered the "best" of Task 1, with Subject 10, the "worst" of Task 1, we can see they show very similar Amplitude, Asymptote and even Rate for their behavioural data. The same phenomenon can also be noticed in Task 3. This might be due to the fact that five trials may not be enough to accurately assess the parameters necessary for a valid learning curve to a satisfying degree.

What is also interesting within the behavioural data, is that all subjects except Subject 5, improved after the first trial. This general universal improvement is especially interesting, since no clear other simultaneous change can be seen between trials, apart from the general trend of improvement. What can be seen as a rather universal change is that all subjects exhibit a sudden increase in movement time for one trial, although having shown improvement prior to this instance. Furthermore, afterwards, all subjects, except Subject 5 who seemed to end on this phenomenon, showed levels of skill comparable to the improvement recorded before the instance. This might further support the suggestion that one path is more challenging than the others, although the intensity of this effect is very subject dependent, as Subject 7 and 8 barely increased their movement time during this supposedly more difficult path.

Task 3 results appeared similar to Task 1 in terms of initial starting differences. The slowest performing subject during trial 1, Subject 7, had a MT of 475.59 more than Subject 4, the fastest performing one, almost double their duration. What is prominently different from Task 1, is the fact that all subjects showed improvement in their MT by the last trial. However, there are different trends to be observed. Interestingly, all subjects, except Subject 3, 5 and 9, show consistent improvement over the course of the task. Subjects 3 and 5 do show improvement between trial 1 and 2, but increase their MT in trial 3 again, although they still showed improvement when comparing trial 1 and 3. Subject 9 on the other hand slightly increased their MT between trial 1 and 2, while then showing improvement between trial 2

and 3, also with an overall improvement when comparing the first and last trial. Nonetheless, the biggest improvement was still between trial 1 and 2, once more supported by the linear mixed model output, estimating the change at 112.4, compared to the estimation of 52.7 between trial 2 and 3.

The learning curves created based on the behavioural data further support the assumptions made about the learning progress of subjects. During Task 1, the Amplitude parameter of the subjects is highly irregular, with Subject 3 seemingly showing the least skill during initial testing, while Subject 7 shows the most sophisticated bronchoscopy skills at the beginning of the experiment. As Amplitude gives us an indication of starting potential, a possible explanation for this discrepancy might be previous experience. Given only novices were recruited for this experiment, no subject had previous bronchoscopy skills training. Therefore, this irregularity in initial experience might be due to personal choices, e.g. playing video games or an instrument. The other parameters, Asymptote and Rate, seemed to be relatively consistent in-between subjects, with Subject 6 having the highest potential Rate of improvement, while Subject 4 showed the least drastic change. During Task 3, learning curves had to rely on an even smaller amount of data than Task 1. Here, all parameters greatly differed between subjects, especially in terms of initial skills (Amplitude) as well as maximum possible performance (Asymptote). The setup of the tasks itself might have played a role in this, as Task 1 still relied on randomly assigned paths while Task 3 presented the subjects with identical trials each time. One might argue that therefore, Task 3's setup was better suited for creating learning curves, although with lack of a sufficient trial number to see significant effects. However, as mentioned before, the data within the behavioural set was too limited, in order to create valid learning curves for the subjects.

Regarding the acceleration data, it has proven to be difficult to relate X-axis acceleration to a significant learning effect. Initially assumed to have a negative influence with increased intensity, all subjects differed greatly in their acceleration across trials, with no clear trends signalling a relationship between improvement and the measured parameter. Subjects who performed very similarly in terms of MT did not reflect this by exhibiting comparable acceleration within tasks. Subject 1 and 7 for example, both very strong performers in Task 1, differed greatly in their acceleration over the course of the trials, with Subject 7 not showing much change of nor initial acceleration, while Subject 1 started the trials with high acceleration potential, and ended with a skew towards rather small potential. This might be due to the reason that Subject 7 initially might have shown high efficiency through little change in acceleration potential, arguably through previous experience in areas

like instruments or gaming, while Subject 1 gradually became more efficient after multiple repetitions. This theory, however, is flawed by the fact that Subject 1 in fact increased their movement time during later trials compared to the first two. Task 3 showed similar results. This indicates that there is no apparent relationship between acceleration and decrease in movement time during bronchoscopies in this experiment.

What stands out in all of the data analysed, is the seemingly prominent lack of transferability of skills between Task 1 and Task 3. Previously strong performers of Task 1, for example Subject 7, did not necessarily perform well during Task 3. This is supported also by the learning curves, especially of the behavioural data, showing no consistency within subjects between tasks on the parameters for learning. This might be due to the discrepancy in goals between tasks. Although both tasks used the same tools for assessment, there seems to be no direct transferability between tasks, directly impacting the performance of each subject. Additionally, tasks seem to differ in validity of bronchoscopic skills. Task 1 shows most irregularities within the Amplitude, therefore subjects seemed to initially differ greatly in terms of skills necessary to perform said task, and less so in the other two parameters, showing rather consistent maximum performance and rate of increase between subjects. Task 3 on the other hand displays more consistent parameters of Amplitude and Rate, meaning that subjects seemed to perform on a similar level initially, with a comparable rate of improvement. However, the Asymptote parameter showed the most variety within the task, indicating that individual maximum improvement is very reliant on compatibility with the task. A possible explanation for this could be the tasks themselves. Task 3 is inherently more consistent in itself than Task 1, given Task 1 relies on different movements each trial as path selection was randomised, while Task 3 required the same movements in the same order. This fact could have amplified or dampened learning, something up for debate, as the results of this thesis do not suffice to make accurate statements about this issue. What statement can be made, however, is that there does seem to be a learning effect within all subjects in both tasks. This is supported by the raw behavioural data as well as the LMER analysis, showing that subjects consistently improved, especially between trial 1 and 2 in both tasks. This supports the previously posed hypothesis that all subjects would exhibit somewhat of a learning effect regarding behavioural data. However, this still has to be taken with more than a grain of scepticism, as the learning curves composed during this thesis show results that are more than ambiguous, due to a variety of factors.

4.1 Limitations and future directions

During this Bachelor's thesis, some limitations presented themselves that might be considerable for reproducibility or further research. The most prominent limitations that were noticed during the experiment was the limited size of trials, as well as the lack of counterbalancing of trials, as trial amount was inconsistent between tasks, as well as arguably of changing difficulty. Therefore it might be of benefit to especially standardise the assessment in regards to Task 1, as there seemed to be a path that required more skill than the others. If trials are standardised and counterbalanced, future experiments might be able to compare subjects more accurately. The data obtained from five trials for Task 1, and only three trials for Task 3 respectively, has shown itself to be a limiting factor, especially when learning curves are desired. In the future, one might consider changing the experiment towards implementing 10 trials for each task, which would allow not only for more data analysis, but also for more reliable statements about a subjects' learning process within a task. With 10 trials, not only would the tasks itself be more comparable to one another, but also results would likely include more detailed explanations for the underlying effects. During the data analysis, outputs on the parameters of learning curves showed ambiguous results, most likely due to the lack of instances of data. Another limitation revealing itself during the experiment was the lack of transparency for each of the tasks regarding the simulator. There was no data on the consistency of each task, nor on their psychometric properties themselves. Henceforth, the validity of the tasks measuring bronchoscopic skills within simulators can be debated. This is noticed during Task 1, as differing paths seem to yield different results, therefore making it harder to accurately make statements about the learning that occurs. Lastly, another limitation of this experiment was the lack of chosen parameters when looking at the motion capture data. As only one sensor has been chosen as a tool for acceleration assessment, the resulting data can be described as lacking. If time would have permitted it, it would have been very interesting to include more parameters into the analysis and explore more ways of data analysis with the resulting data.

Therefore, any future attempts at reproducing or continuing this research effort should concentrate on improving the limitations noticed during this thesis. Additionally, it might be very interesting to include more than one parameter of motion capture data into the analysis. A lot of new insights might be gained by not only looking at the cartesian X-Axis, but also at the other two, Y and Z. Building on this improvement, it might also be of interest to not only look at one sensor, but include a whole segment of motion capture data into the project. This might give future researchers new data, arguably better fit for learning curves, as well as

better understanding of the influences regarding acceleration (or any other parameter for that matter) on successful flexible bronchoscopies.

4.2 Conclusion

The results of this thesis reinforce that individual differences in flexible bronchoscopies are numerous and significant. Simulator training may be beneficial but the key component of providing valuable feedback is not apparent. This experiment is the first step in giving objective feedback in terms of movement time and quality of movement. It was shown that learning occurs differently within every individual can be observed, shown by their decrease in movement time over the course of the experiment. The learning curves support this notion, although an improved experiment, especially with increased trial size, might allow for more accurate and empirical statements. Contrary to the initial hypotheses, cartesian x-axis sensor acceleration did not facilitate successful bronchoscopies in any verifiable way, although it is likely that a combination with the remaining axes (Y and Z) would produce meaningful results. Again, still no clear statement may be made, as this experiment cannot be used as evidence to disprove any connection between them. Conclusively, this study is a successful pilot experiment in assessing individual differences and learning effects in novices during a simulated flexible bronchoscopy.

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Appendix

A. Ethical approval and consent form

UNIVERSITY OF TWENTE.
FACULTY BMS

211324 REQUEST FOR ETHICAL REVIEW

Request nr: 211324

Researcher: Chan, R.W.

Supervisor: –

Reviewer: Lubbe, R.H.J. van der

Status: Approved by commission

Version: 2

1. START

A. TITLE AND CONTEXT OF THE RESEARCH PROJECT

1. What is the title of the research project? (max. 100 characters)

`Motor learning performance differences in flexible bronchoscopy` 2. In which context will you conduct this research?

`Master's Thesis`

3. Date of the application

`16-11-2021`

5. Is this research project closely connected to a research project previously assessed by the BMS Ethics Committee?

`Yes`

please provide the ethic request number(s) for the research project(s):

`210390`

B. CONTACT INFORMATION

6. Contact information for the lead researcher

6a. Initials:

`R.W.`

6b. Surname:

`Chan`

6c. Education/Department (if applicable):

`BMS-OMD`

6d. Staff or Student number:

`76682574`

6e. Email address:

`r.w.chan@utwente.nl`

6f. Telephone number (during the research project):

`+31627518056`

6g. If additional researchers (students and/or staff) will be involved in carrying out this research, please name them:

`Schmettow, Martin, m.schmettow@utwente.nl;`
`Groenier, Marleen, m.groenier@utwente.nl;`
`Roggenbuck, Joel,`
`j.roggenbuck@student.utwente.nl; Pertenbreiter, Marcel,`
`m.pertenbreiter@student.utwente.nl; Gerretsen, Eveline,`
`e.gerretsen@maastrichtuniversity.nl`

6h. Have you completed a PhD degree?

```
Yes
```

8. Is one of the ethics committee reviewers involved in your research? Note: not everyone is a reviewer. `No`

C. RESEARCH PROJECT DESCRIPTION

9a. Please provide a brief description (150 words max.) of the background and aim(s) of your research project in non-expert language.

```
The goal of this research project is to assess the
differences in motoric actions in a simulated flexible
bronchoscopy situation. Inspired by theories of Motor
Sequence Learning (MSL), the aim of the study is to
investigate if more complex, multi-faceted skills like
flexible bronchoscopies can be measured in a more
quantifiable and standardized way. This project is
performed in collaboration with TechMed in UT. The research
project is cross-sectional, comparing participants
experienced in flexible bronchoscopies, namely medical
professionals, with amateur participants/learners. The
project will use the Xsens motion capture system, Myo
armband (electromyography and gyroscope) and video capture
for data collection.
```

9b. Approximate starting date/end date of data collection:

```
Starting date: 2021-11-25
End date: 2022-12-30
```

9c. If applicable: indicate which external organization(s) has/have commissioned and/or provided funding for your research.

Commissioning organization(s):

```
Not applicable
```

Funding organization(s):

```
Not applicable
```

2. TYPE OF STUDY

Please select the type of study you plan to conduct:

```
2021-11-17 14:14:28 2/6
    I will be collecting new data from individuals acting as
    respondents, interviewees, participants or informants.
```

4. RESEARCH INVOLVING THE COLLECTION OF NEW DATA

A: RESEARCH POPULATION

20. Please provide a brief description of the intended research population(s):

```
Amateurs: Healthy young adults from 18 to 35 yrs old.
Primarily, students at the University of Twente living
within a 25km radius of campus. An incentive in the form
of SONA credits will be offered to participants.
Professionals: Medical professionals (expected to be
>20s years old). The medical professionals will be
referred from through TechMed.
```

21. How many individuals will be involved in your research?

```
Amateurs: ~10-15 young adults. Professionals:
~10-15 medical professionals
```

22. Which characteristics must participants/sources possess in order to be included in your research? `Subjects are required to meet the following inclusion criteria: a) no history of mental disorder; b) no substance addiction; c) no signs of cognitive impairment and; d) no physical injuries or impairments that might affect performance in a flexible bronchoscopy.`

23. Does this research specifically target minors (<16 years), people with cognitive impairments, people under institutional care (e.g. hospitals, nursing homes, prisons), specific ethnic groups, people in another country or any other special group that may be more vulnerable than the general population? `No`

24. Are you planning to recruit participants for your research through the BMS test subject pool, SONA `Yes`

B. METHODS OF DATA COLLECTION

25. What is the best description of your research?

- `Other`

  `(please provide a brief description of the methods used to generate and/or collect data):`

  `Cross-sectional experimental research`

26. Please prove a brief yet sufficiently detailed overview of activities, as you would in the Procedure section of your thesis or paper. Among other things, please provide information about the information given to your research population, the manipulations (if applicable), the measures you use (at construct level), etc. in a way that is understandable for a relative lay person.

```
Participants will be introduced to the study after
accessing the lab. After being briefed on the study and
its goals, the participants are asked to sign the consent
form. They are fitted with the Xsens motion capture
technology and the Myo armband. After ensuring the
participants are comfortable with the setup, they will be asked
to
```

```
participate in a series of 10 - 15 simulated flexible
bronchoscopy tasks on a bronchoscopy simulator that is
situated in the TechMed centre. After completing the
study itself the participants will be debriefed and
informed of the use and processing of the data.
```

How much time will each participant spend (mention the number of sessions/meetings in which they will participate and the time per session/meeting)?

```
1 session for up to 150 minutes (including Xsens and
Myo setup, bronchoscopy simulator setup and
cleaning).
```

C: BURDEN AND RISKS OF PARTICIPATION

27. Please provide a brief description of these burdens and/or risks and how you plan to minimize them: `For the participants, mental and physical`
```
exhaustion of the trials is the most prominent burden.
However, exhaustion are not beyond the usual training
activities that one would perform in bronchoscopy training
and based on the study design. Additionally, hygiene and
requirements conforming to the current Covid-19 law
regulations will be adhered to. This will be of utmost
importance for both staff and participants. Staff and
participants are required to: 1) Conform to the mask mandate
in place at the time of the experiment; 2) Disinfect every
surface the participant may be in contact with, before and
after the experiment (e.g. tables, chairs, simulator, Xsens
and Myo contact points).
```

28. Can the participants benefit from the research and/or their participation in any way? `Yes`

Please Explain:
```
They gain access to the results of the experiment (once
they are reported in publications), as well as insights
into their own motor and flexible bronchoscopy skills
following completion of the experiment.
```

29. Will the study expose the researcher to any risks (e.g. when collecting data in potentially dangerous environments or through dangerous activities, when dealing with sensitive or distressing topics, or when working in a setting that may pose 'lone worker' risks)?

```
Yes
```

Please Explain:
```
As mentioned in No.27, all people involved will conform to
the current Covid-19 regulations in order to minimise
```

```
transmission of the virus.
```

D. INFORMED CONSENT

30. Will you inform potential research participants (and/or their legal repsentative(s), in case of non competent participants) about the aims, activities, burdens and risks of the research before they decide whether to take part in the research?

```
Yes
```

```
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```
Briefly clarify how:

```
The experiment will be explained briefly without
mentioning exact details to prevent changes in strategic
motoric behaviour. We aim for participants to perform as
naturally as possible during their motor performance. At
the end we will also inform of what will happen with the
data and how it will be used for cognitive modelling of
motor and learning performances.
```

32. How will you obtain the voluntary, informed consent of the research participants (or their legal repsentatives in case of non-competent participants)?

```
Signed
```

33. Will you clearly inform research participants that they can withdraw from the research at any time without explanation/justification?

```
Yes
```

34. Are the research participants somehow dependent on or in a subordinate position to the researcher(s) (e.g. students or relatives)?

```
No
```

35. Will participants receive any rewards, incentives or payments for participating in
the research? • `For student participants: Human research`
`participant credits (if you use the SONA test subject`
`pool)`

36. In the interest of transparency, it is a good practice to inform participants about what will happen after their participation is completed. How will you inform participants about what will happen after their participation is concluded?

```
• Participants will receive oral/written information
  about what the researcher(s) will do with the
  collected data.
```

E. CONFIDENTIALITY AND ANONYMITY

37. Does the data collected contain personal identifiable information that can be traced back to specific individuals/organizations?

```
No
```

39. Will you make use of audio or video recording?

```
Yes
```

> • What steps have you taken to ensure safe audio/video data storage?

```
Videos files are mainly used for comparison with motion
capture data for the comparison of critical movement time
points. All participant video files will be deidentified
and only participant numbers will be used. Video files
will be transferred onto password-locked, networked UT
computers in the Faculty of BMS for storage and analysis.
Once transferred, the original footage will be deleted on
          the original recording device. Only the principle
      investigators will have access to this video footage.
```

```
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```

> • At what point in the research will tapes/digital recordings/files be destroyed?

```
The digital recordings will be destroyed once the results
          have been published or within 10 years of the data
              collection (whichever that arises earlier).
```

5. DATA MANAGEMENT

```
  • I have read the UT Data policy.
  • I am aware of my responsibilities for the proper
     handling of data, regarding working with personal
     data, storage of data, sharing and
     presentation/publication of data.
```

6. OTHER POTENTIAL ETHICAL ISSUES/CONFLICTS OF INTEREST

40. Do you anticipate any other ethical issues/conflicts of interest in your research project that have not been previously noted in this application? Please state any issues and explain how you propose to deal with them. Additionally, if known indicate the purpose your results have (i.e. the results are used for e.g. policy, management, strategic or societal purposes).

```
No.
```

7. ATTACHMENTS

```
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```

8. COMMENTS

```
  -
```

9. CONCLUSION

Status: `Approved by commission`

The BMS ethical committee / Domain Humanities & Social Sciences has assessed the

ethical aspects of your research project. On the basis of the information you provided, the committee does not have any ethical concerns regarding this research project. It is your responsibility to ensure that the research is carried out in line with the information provided in the application you submitted for ethical review. If you make changes to the proposal that affect the approach to research on humans, you must resubmit the changed project or grant agreement to the ethical committee with these changes highlighted. Moreover, novel ethical issues may emerge while carrying out your research. It is important that you re consider and discuss the ethical aspects and implications of your research regularly, and that you proceed as a responsible scientist.

Finally, your research is subject to regulations such as the EU General Data Protection Regulation (GDPR), the Code of Conduct for the use of personal data in Scientific Research by VSNU (the Association of Universities in the Netherlands), further codes of conduct that are applicable in your field, and the obligation to report a security incident (data breach or otherwise) at the UT.

```
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UNIVERSITY OF TWENTE.

PARTICIPANT INFORMATION SHEET

Research Project Title: Motor learning performance differences in flexible bronchoscopy

This project has been approved by the University of Twente's Behavioral, Management and Social sciences (BMS) Ethics Committee No. 211324.

Researcher Contact details: Supervisor Contact details:

Joel Roggenbuck
Email:j.roggenbuck@student .utwente.nl
Phone:
+4915730192897 or

Marcel Pertenbreiter
Email:m.pertenbreiter@stud ent.utwente.nl
Dr. Russell Chan (Ph.D) Faculty of BMS Email:
r.w.chan@utwente.nl Phone: +31534896867

Invitation to participate in the study: You are hereby invited to participate in our study about motor performance differences in flexible bronchoscopy. The participation is entirely voluntary, and withdrawal from the study is possible at any given point in time during the study. Additionally, a written consent to participate is required prior to the beginning of the experiment.

Purpose of the study: The study is designed to assess differences in motor performance of participants in a simulated flexible bronchoscopy setting. It aims at finding key differences in behavior between participants without bronchoscopy skills and experienced individuals through motion capture technology. Ideally, these insights may be used to improve the learning process and objectifying learning parameters for future bronchoscopy within the profession.

Eligibility to participate: In order to participate, you must meet the following eligibility criteria: ● You are aged between 18 and 35 years

● You are not currently taking any prescribed medication on a regular basis (birth contraceptives excluded)

● You are not physically injured

● You do not have any learning disabilities, 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 are comfortable to attend 1 session of data collection for up to 3 hours. ● You do not mind having motion capture sensors attached to your body (primarily upper body).

● You are feeling generally well.

UNIVERSITY OF TWENTE.

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

Requirements:

Participation in the study involves attending a laboratory session <u>ONCE </u>for up to 3-hour research.

What is Xsens and Myo 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.

The Myo is an armband that is worn on the forearms. It captures electromyography (muscle

activations) and also gyroscopic parameters for understanding the orientation of and positioning of the arm during the bronchoscopy performance.

Lab Session (~3 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 station, which is connected to the stimulus pc. Once the equipment 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 minutes. After this, you will perform a stepping task in which you train motor sequence and a testing block. 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. 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.

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, Cubicus (building no. 41), room B320, 7522 NB Enschede The Netherlands) and on secured electronic storage housed within the University of Twente, BMS Labs.

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.

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Consent Form for Motor learning performance differences in flexible bronchoscopy

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 video recording, Xsens and Myo armband.

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

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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

B. Procedure Protocol

Simulated Flexible Bronchoscopy Study

Before the day of the experiment

Send this message to the participant either via sona systems or email.

Dear participant,

Thank you for taking part in our study. We would like to give you some information beforehand.

We are interested in individual differences of body position when performing a simulated bronchoscopy. For that purpose, you will be required to wear Xsens motion sensors on your whole body. For that, you will be asked to wear a special t-shirt, gloves and a headband, as well as velcro straps around your arms, legs and feet. While this may sound uncomfortable, rest assured that all researchers were very comfortable in the setup during trial sessions! For hygienic reasons, please wear a t-shirt or undershirt below on the day of the experiment. Additionally, to ensure the sensors can be securely fit to you and won't fall off during the trials, please wear somewhat tight fitting clothing when coming to the experiment.

The study will take a maximum of 2 ½ hours. This also includes the time to inform you about the task and to set up the equipment. Also, different measurements will be taken, for example your body height, shoe size and related biomechanical measurements. Please be aware that you should not consume any alcohol or other drugs prior to the experiment. You should also not be physically injured and you should not currently be taking any prescribed medication to control for balance or vestibular problems on a regular basis (oral or implanted birth contraceptives are fine).

We look forward to seeing you!

Kind regards,

Joel Roggenbuck

On the day of the experiment

A	Preparation
1	Check if all equipment is present (See equipment list)
2	Start the main laptop and set up the GoPro
3	Open all necessary software (OBS Studio, MVN Analyze, Myo Script) and start up the simulator by first switching the red "OFF/ON" switch to "ON" at the back of the simulator, followed by pressing then red "PC ON" button at the front of the simulator (below the "GI-BRONCH mentor" logo). Also connect the BRONCH scope (not the GI scope) to the simulator, by connecting the scope side connector exactly in the prongs and recesses of the system side connector (see images below). Turn the silver thing clockwise until you hear a "click". Wait until the MentorLearn application starts, this happens by default after +- 5 minutes,

so do **not** start the app yourself. Note: sometimes the app unfortunately does not start, probably due to a bug. If that occurs, even after waiting for 10 minutes, first press the "PC ON" button for a few seconds, followed by pressing the "OFF/ON" switch to "OFF". Wait a few seconds, switch the red "OFF/ON" switch to "ON" and press the "PC ON" button.

As soon as the MentorLearn app has started, log in (user name and password are both your last name started with capital letter + first letter of first name E.g.: GerretsenE). Then, go to BRONCH Mentor, click on Essential Bronchoscopy. Here you can find Task 1 until Task 5. For this study, we only use Task 1 – Basic Scope Manipulation and Task 3 – Lung Anatomy, Bronchial Segments.

4	Open the Xsens backpack and place the necessary velcro tapes, t-shirts, headbands and gloves on the desk.
B	**Welcome the participant**
1	Greet Participant in front of the room. Introduce yourself and let them store their belongings on the table next to the simulator but remind them to bring their water bottle/drink and disinfect their hands.
3	Let the Participant read the information sheet and sign the form of informed consent (This is separate forms that we submitted and approved from Ethics)
4	Move along to the Xsens gear with the participant. (Checking setup)
C	**Preparation of the participant and MVN gear.**
1	Inform the participant about the necessity of the Xsens gear for the study, explain the uses, how many sensors and where they will be attached. (Give the opportunity for questions for the participants.)
2	Insert the sternum sensor into the t-shirt (give the appropriate sized t-shirt) and ask the participant to put on the shirt. Insert head sensor into headband and hand sensors into gloves, while participants changes
3	Attach velcro tape and rest of sensors in coherence with the placement shown in the manual picture and ask the participants to put on the headband and gloves.

((IMPORTANT: Tape should always be **COVERING** the sensors.// Do not forget feet))

4	Take measurements to fill in MVN analyze pro. (Body height, feet length) **For shoe size to feet length, see chart below**
5	Explain the calibration procedure to the participant.
6	Go through with the calibration, achieve a good quality estimate. (Repeat if necessary)
D	**Setup of Myo Gesture Control Armband**
1	Demonstrate the Myo armband to the participants, explain its uses, and state what data is going to be sensed (EMG and IMU)
2	Open the software 'Myo Connect'
3	Put the Myo on the forearm that is used to handle the bronchoscope.
4	Explain to the participants the required hand and arm movements to synchronize the Myo.
5	Let the participants perform the required movement.
6	The Myo requires time to warm up. After the Myo has warmed up, perform the sync movement again for more accurate muscle sensing.
E	*Setup of MATLAB (Myo Script) with OBS and Xsens*
1	Open MATLAB on the secondary screen
2	Open the Xsens software and OBS on the main screen and place Xsens on the right side of the screen and OBS on the left side.

2	On default, the correct folder should be open in MATLAB (…/MATLAB\MyoMex-master\MyoMex). Should this not be the case, then you should add the folder into the "current folder" section, which you can find on the left side of MATLAB).
3	Head to the data collection folder and open the folder corresponding to your current participant number. Within this folder, there are the main scripts for the data collection. One script corresponds to Task 1, the other to Task 3.
4	MATLAB navigates through OBS and Xsens by taking control over the keyboard and mouse functions. In order for MATLAB to click on the correct buttons (E.g., the OBS record button), you need to specify the x- and y-location in relation to the size of the display in use. The following files need to be adapted accordingly: StartRecord_Reframe.m StopRecord.m XsensSetMarkerStop.m XsensSetMarkerStart.m
F	*Data collection*
1	Introduce the participant to the simulator. Explain that the simulator and bronchoscope should be handled very carefully; especially the tip of the bronchoscope is very fragile and expensive. Explain that the bronchoscope should be held in the dominant hand. The non-dominant hand can be used to insert the distal part of the bronchoscope in the "mouth" of the simulator (but do not ask the participant yet to insert the scope). Ask the participant to stand in "Practice position" as shown in the left picture. Let the participant practice how to control the tip of the bronchoscope, by making movements with his/her dominant hand, wrist and thumb (on the steering lever). Explain that in principle all movements should be made by using the wrist and thumb, and not the lower arm. *Practice position* *Inserting position* While inserting the bronchoscope, the participant needs to stand right behind the "head of the simulator", while keeping the black insertion cord as vertical as possible. This is

	shown in the right picture, "Inserting position". Note: do **not** insert the bronchoscope before the simulator task is started and the screen displays "Introduce the scope orally"; in this step, you simply explain how to do it.
2	Explain the procedure and tasks of the experiment
3	Answer any remaining questions.
3	Ask the participant to stand in front of the simulator and start up trial task
4	Align X-axis and position in MVN Analyze. Start the recording on both OBS Studio and MVN Analyze and hand the bronchoscope to the participant.
!!!! ! ! ! ! ! ! ! ! ! ! ! ! ! ! !!!!	**GUIDE: SETTING MARKERS** ((Have one Researcher loudly announce the following in bold)) . . . **READY** (participant is ready to start task) → <u>Run Myo Script </u>(Section: Stop and Start Streaming) . . . **START** (participant passes the start line) → <u>Run Myo Script </u>(Section: Stop and Start Streaming) . . . **END** (participant finishes task) → <u>Run Myo Script </u>(Section: Stop and Start Streaming)
5	Start Practice Task 1
6	Let Participant know the next trial will start actual testing period.
7	Go on Matlab ☐ Run Myo Script (Section: Initialize the Myo Data Collection) of the file corresponding to Task 3.
8	Start Task 1 Trial 1 - Run Myo Script (Section: Stop and Start Streaming). After the run, make a **picture** from the simulator metrics that appear on the bottom right of the screen.
9	(The MVN Recording will be stopped automatically) → Save File with Comment Task 1 Trial 1.
10	Start Task 1 Trial 2 - Run Myo Script (Section: Stop and Start Streaming). After the run, make a **picture** from the simulator metrics that appear on the lower right of the screen.
11	(The MVN Recording will be stopped automatically) → Save File with Comment Task 1 Trial 2
12	Start Task 1 Trial 3 - Run Myo Script (Section: Stop and Start Streaming). After the run, make a **picture** from the simulator metrics that appear on the lower right of the screen.
13	(The MVN Recording will be stopped automatically) → Save File with Comment Task 1

	Trial 3.
14	Start Task 1 Trial 4 - Run Myo Script (Section: Stop and Start Streaming). After the run, make a **picture** from the simulator metrics that appear on the lower right of the screen.
15	(The MVN Recording will be stopped automatically) → Save File with Comment Task 1 Trial 4.
16	Start Task 1 Trial 5 - Run Myo Script (Section: Stop and Start Streaming). After the run, make a **picture** from the simulator metrics that appear on the lower right of the screen.
17	Save Myo File – Run Myo Script (Section: Save the file and the variables) ⬜ Do not forget to indicate the correct filename!
18	Run Myo Script (Section: Clear the variables from the workspace and delete connection to Myo)
19	(5 minute break.) (The MVN Recording will be stopped automatically) → Save File with Comment Task 1 Trial 5. Prepare the next trial session on the laptop. Click on "Finish" on the bottom right of the simulator screen. Next, click **Yes** when "Do you want to save performance?" appears on the screen.
20	Demonstrate Task 3 to the participant in full. Fully retract the scope and click on "Finish" on the bottom right of the simulator screen. Next, click **No** when "Do you want to save performance?" appears on the screen.
21	Ask the participant to resume spot, answer any remaining or new questions
22	Go on Matlab ⬜ Run Myo Script (Section: Initialize the Myo Data Collection) of the file corresponding to Task 3.
23	Start Task 3 Trial 1 - Run Myo Script (Section: Stop and Start Streaming). When the participant has reached the final segment of the left lower lobe, click on "Finish" on the bottom right of the simulator screen. Next, click **Yes** when "Do you want to save performance?" appears on the screen.
24	(The MVN Recording will be stopped automatically) → Save File with Comment Task 3 Trial 1.
25	Start Task 3 Trial 2 - Run Myo Script (Section: Stop and Start Streaming). When the participant has reached the final segment of the left lower lobe, click on "Finish" on the bottom right of the simulator screen. Next, click **Yes** when "Do you want to save performance?" appears on the screen.
26	(The MVN Recording will be stopped automatically) → Save File with Comment Task 3 Trial 2.
27	Start Task 3 Trial 3 - Run Myo Script (Section: Stop and Start Streaming). When the participant has reached the final segment of the left lower lobe, click on "Finish" on the bottom right of the simulator screen. Next, click **Yes** when "Do you want to save performance?" appears on the screen.

28	Save Myo File – Run Myo Script (Section: Save the file and the variables) ☐ Do not forget to indicate the correct filename!
29	Run Myo Script (Clear the variables from the workspace and delete connection to Myo)
30	(The MVN Recording will be stopped automatically) → Save File with Comment Task 3 Trial 3.
G	***Debriefing/ data storage***
1	Let the participant take off the Xsens gear. Store it. Check all the inventory gear.
2	Debrief Participant and thank them for participation.
3	Open recording in MVN Analyze reprocess on normal quality and export as MVNX file. Load it on the hard drive. Load the behavioral data on the hard drive.
4	Put a USB stick in the USB port of the simulator, located somewhat below the "ON/OFF" switch. On the simulator screen, go to "Reports", "BRONCH mentor" and tick the top 4 reports boxes (1 time task 1 and 3 times task 3). Note: since the touch screen is not calibrated perfectly, it is recommended to use the track ball on the keyboard to select. Then, click on the three dots in the right top of the screen, click on "Export Performance". Select "rows with details export" as the Selected Format. Click on "Export". Type a suitable name in the File name field, followed by **.zip** .
5	To turn off the simulator, click "Logout", "Shut down" and press the "ON/OFF" switch

C. Syntax

##Packages

library(lme4)
library(effects)
library(lattice)
library(car)
library(ggplot2)
library(knitr)
library(reshape2)
library(dplyr)
library(forcats)
library(DHARMa)
library(Hmisc)
library(phia)
library(lsmeans)
library(emmeans)
library(multcomp)
library(plotly)
library(lmerTest)
library(readxl)
library(tinytex)

#Task 1 Model

```r
m.df1 <- lmer(Movement_Time ~ Trial + (1|Participant), data=df1, REML = FALSE)
Anova(m.df1)

#Task 3 Model
m.df3 <- lmer(Movement_Time ~ Trial + (1|Participant), data=df3, REML = FALSE)
Anova(m.df3)

 #Some options
#Holm Contrasts
#https://stats.stackexchange.com/questions/237512/how-to-perform-post-hoc-test-on-lmer-model

#Interpretation from Summary of T values
#https://stats.stackexchange.com/questions/87412/how-to-interpret-2-way-and-3-way-interaction-in-lmer/87415

#summary(glht(m.AF_WO, linfct = mcp(Group = "Tukey")), test = adjusted("holm"))
#plot(emmeans(m.AF_WO2, ~ Group | Session))

#Task 1 model post hoc
summary(glht(m.df1))

#Options
#Ordering timepoint if needed
#ae.m.df.AF2$Time <- factor(ae.m.df.AF2$Time, levels=c('1', '2', '3', '4', '5', '6', '7', '8', '9', '10'))

#Task 1 Model effects
ae.m.df1 <- allEffects(m.df1)
ae.m.df.df1 <- as.data.frame(ae.m.df1[[1]])

#Task 3 Model effects
ae.m.df3 <- allEffects(m.df3)
ae.m.df.df3 <- as.data.frame(ae.m.df3[[1]])

#Task 1 plot
ae.Task1<-ggplot(ae.m.df.df1, aes(x=Trial,y=fit,color=Trial))+
 geom_errorbar(aes(ymin=lower, ymax=upper), width=.1) +
 geom_line() +
 geom_point()+
 ylab("Movement Time (Seconds)")+
 xlab("Trial")+
 ggtitle("Movement Time ~ Trial")+
 theme_light()

plot(ae.Task1)

#Task 3 plot
ae.Task3<-ggplot(ae.m.df.df3, aes(x=Trial,y=fit,color=Trial))+
 geom_errorbar(aes(ymin=lower, ymax=upper), width=.1) +
 geom_line() +
 geom_point()+
 ylab("Movement Time (Seconds)")+
 xlab("Trial")+
 ggtitle("Movement Time ~ Trial")+
 theme_light()
```

```
plot(ae.Task3)
```

FREE LEARNING CURVES

##Packages that are required for the analysis

```r
library(tidyverse)
library(broom.mixed)
library(devtools)
library(brms)
library(mascutils)
library(bayr)
library(readxl)
library(ggplot2)
library(effects)



# Free learning curve 1
# per subject per sequence
df1 %>%
  ggplot(aes(x = Trial,
        y = MT,
        color=Subject)) +
  geom_point() +
  geom_smooth(se = F) +
  facet_wrap(~Subject, scales = "free_y")+
  ylab("MT (s)")+
  xlab("Time")+
  ylim(0,250)+
  theme_classic()+
  scale_color_manual(values=mycolors)

df3 %>%
  ggplot(aes(x = Trial,
        y = MT,
        color=Subject)) +
  geom_point() +
  geom_smooth(se = F) +
  facet_wrap(~Subject, scales = "free_y")+
  ylab("MT (s)")+
  xlab("Time")+
  ylim(250,1000)+
  theme_classic()+
  scale_color_manual(values=mycolors)

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

df1 %>%
  ggplot(aes(x = Trial,
        y = MT,
        group = Subject,
        color= Subject)) +
  geom_smooth(se = F)+
```

```r
  #scale_x_continuous(limits = c(0,192), expand = c(0, 0))+
  theme_classic()+
  ylab("MT (s)")+
  xlab("Time")+
  scale_color_manual(values=mycolors)+
  facet_wrap(~Trial)

#Over Trials / TimeRepX
df1 %>%
  ggplot(aes(x = Rep,
         y = MT,
         group = Subject,
         color=Subject)) +
  geom_smooth(se = F)+
  #scale_x_continuous(limits = c(0,192), expand = c(0, 0))+
  theme_classic()+
  ylab("MT (s)")+
  xlab("Rep")+
  scale_color_manual(values=mycolors)+
  facet_wrap(~Subject)

df3 %>%
  ggplot(aes(x = Rep,
         y = MT,
         group = Subject,
         color=Subject)) +
  geom_smooth(se = F)+
  #scale_x_continuous(limits = c(0,192), expand = c(0, 0))+
  theme_classic()+
  ylab("MT (s)")+
  xlab("Rep")+
  scale_color_manual(values=mycolors)+
  facet_wrap(~Subject)

## NON-LINEAR MULTILEVEL REGRESSION ##

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

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 <-
  df1 %>%
  brm(bf(F_ary,
       flist = F_ary_ef_1,
       nl = T),
     prior = F_ary_prior,
```

```r
     family = "exgaussian",
     data = .,
     iter = 10,
     warmup = 8,
     save_pars=save_pars("Subject"))
```

LEARNING CURVES BASED ON MODEL ESTIMATES
```r
df1$Subject<-df1$Subject
# learning curves per Subject
df1 %>%
  mutate(M_1 = predict(PP_1)$center) %>%
  ggplot(aes(x = Rep,
         y = M_1,
         color=Subject)) +
  facet_wrap(~Subject, scales = "free_y") +
  geom_smooth(se = F) +
  geom_point(alpha=0.2, size=1)+
  ylim(-100,500)+
  labs(x="Rep",y="Model estimates")+
  theme_classic()+
  scale_color_manual(values=mycolors)
```

```r
# crossbar plots for each parameter and Subject
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_classic()
```

NON-LINEAR MULTILEVEL REGRESSION

```r
# specify formula, variables and weakly informative priors
F_ary2 <- formula(MT ~ asym + ampl * exp(-rate * Rep))


F_ary_ef_2 <- list(formula(ampl ~ 1|Subject),
           formula(rate ~ 1|Subject),
           formula(asym ~ 1|Subject))


F_ary_prior2 <- 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_2 <-
  df3 %>%
  brm(bf(F_ary2,
     flist = F_ary_ef_2,
     nl = T),
```

```
   prior = F_ary_prior2,
   family = "exgaussian",
   data = .,
   iter = 10,
   warmup = 8,
   save_pars=save_pars("Subject"))

## LEARNING CURVES BASED ON MODEL ESTIMATES ##
df3$Subject<-df3$Subject
# learning curves per Subject
df3 %>%
  mutate(M_2 = predict(PP_2)$center) %>%
  ggplot(aes(x = Rep,
         y = M_2,
         color=Subject)) +
  facet_wrap(~Subject, scales = "free_y") +
  geom_smooth(se = F) +
  geom_point(alpha=0.2, size=1)+
  ylim(-500,1500)+
  labs(x="Rep",y="Model estimates")+
  theme_classic()+
  scale_color_manual(values=mycolors)

# crossbar plots for each parameter and Subject
P_2 %>%
  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_classic()
```

Learning Curves Acceleration Task 1

##Packages that are required for the analysis

```
library(tidyverse)
library(broom.mixed)
library(devtools)
library(brms)
library(mascutils)
library(bayr)
library(readxl)
library(ggplot2)
library(effects)
```

```
dfAcc2$Participant <- factor(dfAcc2$Participant)
```

```r
mycolors=c("#6b5f3c","#ccc627","#54ab8e","#587ed1","#b04366","#de2d26","#d95f0e", "#a1d99b", "#dd1c77",
"#a6bddb")


## FREE LEARNING CURVES ##

# Free learning curve 1
# per subject per sequence
dfAcc2 %>%
  ggplot(aes(x = Time,
         y = DomHand_X,
         color=Participant)) +
  geom_point() +
  geom_smooth(se = F) +
  facet_wrap(~Participant, scales = "free_y")+
  ylab("DomHand Acc")+
  xlab("Time")+
  #ylim(0,1.288)+
  theme_minimal()+
  scale_color_manual(values=mycolors)

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

dfAcc2 %>%
  ggplot(aes(x = Time,
         y = DomHand_X,
         group = Participant,
         color=Participant)) +
  geom_smooth(se = F)+
  #scale_x_continuous(limits = c(0,192), expand = c(0, 0))+
  theme_classic()+
  ylab("DomHand_X")+
  xlab("Time")+
  scale_color_manual(values=mycolors)+
  facet_wrap(~Trial)

#Over Trials / TimeRepX
dfAcc2 %>%
  ggplot(aes(x = TimeRepX,
         y = DomHand_X,
         group = Participant,
         color=Participant)) +
  geom_smooth(se = F)+
  #scale_x_continuous(limits = c(0,192), expand = c(0, 0))+
  theme_classic()+
  ylab("DomHand_X")+
  xlab("Time")+
  scale_color_manual(values=mycolors)+
  facet_wrap(~Participant)

## NON-LINEAR MULTILEVEL REGRESSION ##

# specify formula, variables and weakly informative priors
```

```r
F_ary <- formula(DomHand_X ~ asym + ampl * exp(-rate * TimeRepX))


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


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 <-
  dfAcc2 %>%
  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("Participant"))

## LEARNING CURVES BASED ON MODEL ESTIMATES ##
dfAcc2$Participant<-dfAcc2$Participant
# learning curves per participant
dfAcc2 %>%
  mutate(M_1 = predict(PP_1)$center) %>%
  ggplot(aes(x = TimeRepX,
        y = M_1,
        color=Participant)) +
  facet_wrap(~Participant, 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_classic()+
  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_classic()
```

Learning Curves Acceleration Task 3

Packages that are required for the analysis

```
library(tidyverse)
library(broom.mixed)
library(devtools)
library(brms)
library(mascutils)
library(bayr)
library(readxl)
library(ggplot2)
library(effects)

dfAcc3$Subject <- factor(dfAcc3$Subject)
mycolors=c("#6b5f3c","#ccc627","#54ab8e","#587ed1","#b04366","#de2d26","#d95f0e", "#a1d99b", "#dd1c77",
"#a6bddb")


## FREE LEARNING CURVES ##

# Free learning curve 1
# per subject per sequence
dfAcc3 %>%
  ggplot(aes(x = Time,
        y = DomHandX,
        color=Subject)) +
  geom_point() +
  geom_smooth(se = F) +
  facet_wrap(~Subject, scales = "free_y")+
  ylab("DomHand Acc")+
  xlab("Time")+
  #ylim(0,1.288)+
  theme_minimal()+
  scale_color_manual(values=mycolors)

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

dfAcc3 %>%
  ggplot(aes(x = Time,
        y = DomHandX,
        group = Subject,
        color= Subject)) +
  geom_smooth(se = F)+
  #scale_x_continuous(limits = c(0,192), expand = c(0, 0))+
  theme_classic()+
  ylab("DomHand_X")+
  xlab("Time")+
  scale_color_manual(values=mycolors)+
  facet_wrap(~Trial)

#Over Trials / TimeRepX
dfAcc3 %>%
  ggplot(aes(x = TimeRepX,
        y = DomHandX,
```

```r
        group = Subject,
        color=Subject)) +
  geom_smooth(se = F)+
  #scale_x_continuous(limits = c(0,192), expand = c(0, 0))+
  theme_classic()+
  ylab("DomHand_X")+
  xlab("Time")+
  scale_color_manual(values=mycolors)+
  facet_wrap(~Subject)

## NON-LINEAR MULTILEVEL REGRESSION ##

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

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 <-
  dfAcc3 %>%
  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"))

## LEARNING CURVES BASED ON MODEL ESTIMATES ##
dfAcc3$Subject<-dfAcc3$Subject
# learning curves per Subject
dfAcc3 %>%
  mutate(M_1 = predict(PP_1)$center) %>%
  ggplot(aes(x = TimeRepX,
         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_classic()+
  scale_color_manual(values=mycolors)

# crossbar plots for each parameter and Subject
P_1 %>%
```

```r
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_classic()
```