Experience in Flexible Bronchoscopy: Exploring the Motor Skill Performance of Novices, Intermediates, and Experts

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Abstract

Introduction: Deciding when a doctor can perform bronchoscopy on patients without assistance and supervision is done through the assessment of experts. Recruiting experienced bronchoscopist is costly. Besides, the quality of evaluation differs between experts and might be subjective. The first goal of the current study is to find behavioural markers for level of expertise which can distinguish between expert, intermediate, and novice bronchoscopists. Since successful bronchoscopy mainly depends on the handling of the bronchoscope, the study investigated the movement of the hand, forearm, and upper arm for each proficiency. The second aim of this study was to use the behavioural characteristics to model learning curves, which could then be applied to predict expertise based on the amount of training.

Method: 30 participants were involved in this study. The study made use of a between-subject design investigating the difference between experts, intermediates, and novices. Each participant completed two tasks on a bronchoscopy simulator while wearing a motion tracking suit to record their movement. Movement was measured in the form of acceleration and velocity. In addition, performance measures, including the completion time and the number of mistakes, were obtained from the simulator.

Results: The estimation of learning curves was unsuccessful. The focus was on exploring qualitative differences of movement and performance. Therefore, generalised linear regression models were used. Intermediates reported the highest values for acceleration and velocity followed by the experts and novices. The experts have the lowest completion time for the first task despite making more mistakes than the intermediates. The experts mainly move their hand and arm from left to right with constant speed and accelerate forwards and backwards. For the intermediates it is the other way around. In line with the expectations, the novices took the longest to complete the tasks and made the most errors.

Discussion: We gave justification on why experts move slower than intermediates. Next, the type of movement that characterises an expert bronchoscopist was described more thoroughly. The novices did not show any sign of exponential learning. Thus, their movement has been analysed by investigating the factors that could inhibit beginner bronchoscopist from making learning progress.

1. Introduction

1.1 The need for improved bronchoscopy training

The medical procedure known as bronchoscopy is applied to inspect a person's lungs and air passages for diagnostic purposes (Prakash, 1999). The process consists of an instrument, the bronchoscope, which is inserted into the person's airways through the mouth or nose. The operator can guide the bronchoscope through the lung passages externally by controlling a device handle, the flexible scope, placed in their hands (Prakash, 1999). Overall, bronchoscopy is associated with a low probability of complications. In a study by Jin et al. (2008), they inspected 23862 cases of bronchoscopy. They discovered that about 152 subjects experienced severe complications making up 0.637%, with three cases resulting in death leading to a mortality rate of 0.013%. Exclusively experienced bronchoscopists performed these bronchoscopies. In comparison to experienced bronchoscopists, the complication rate of inexperienced bronchoscopists is almost five times as high, according to a study by Stather et al. (2013). Besides, the procedure time is significantly longer, with about 37 minutes for experts and 58 minutes for novices (Stather et al., 2013). The reason that beginners can perform bronchoscopy on actual patients, in the first place, is for training purposes. They learn to perform bronchoscopy by operating on patients under the supervision of an expert. Considering the possible consequences for the patient, this training method - termed the apprenticeship model - has been increasingly regarded as problematic and unethical (Follmann, Pereira, Knauel, Rossaint, & Czaplik, 2019).

Simulation training has been developed as a more ethical and efficient training method that allows novices to practice their skills to gain proficiency. The simulator comes with multiple advantages in comparison to traditional methods. First, there is no risk of harm in the procedure as it would be with actual patients. Second, unlike medical phantoms, the simulator can provide more accurate feedback for inadequate performance (Follmann et al., 2019). As an illustration, medical phantoms can indicate when the bronchoscope has damaged tissue. The simulator takes it a step further by highlighting how long the bronchoscope's tip collided with the bronchial wall (Kastelik et al., 2013). Only high-fidelity simulators offer these advanced feedback options. Low-fidelity bronchoscopy simulators are far less developed and do not offer similarly detailed feedback (Stather, Lamb, & Tremblay, 2011). Third, simulators can provide numerous data that would be unobtainable with operations on real-life patients, including a performance score and information on how well the operator navigated through the airways (Kastelik et al., 2013). Finally, since simulator training is not reliant on the presence of patients for the trainee to get feedback, they are well suited for research purposes that depend on extensive data collection.

1.2 The Apprenticeship Model

Despite these improvements to traditional methods, there remain some issues. It is difficult to assess the amount of training after a bronchoscopist is sufficiently competent to perform on actual patients. That is due to a lack of objective criteria defining competency (Davoudi & Colt, 2009). The current approach to estimating competency is based on the subjective assessment and evaluation of experienced bronchoscopist either during training with the simulator or during supervised examinations of patients (Davoudi & Colt, 2009). Other pulmonologists conduct expert judgements despite their tight time schedules and responsibilities. Recruiting these experts costs them valuable time, and the organisation, whether the government or the hospital itself, needs to compensate their labour financially. For instance, in the United Kingdom, a recommended 100 flexible bronchoscopies must be supervised before the bronchoscopist can perform on patients independently (British Thoracic Society Bronchoscopy Guidelines Committee, 2001). For each of these bronchoscopies, an expert is present to evaluate the performance and secure the patient's safety. Hence, experts' evaluation is inefficient in the long run considering that substantial human resources are required.

Expert judgement might also be highly subjective as the experts have developed distinctive approaches to bronchoscopy (Konge, Arendrup, Von Buchwald, & Ringsted, 2011). Besides being subjective, expert assessment is not a scientifically validated method (Konge et al., 2011). In other words, experts could have different opinions or biases on the aspects that characterise an expert bronchoscopist impeding the establishment of objective guidelines.

It has been proposed that experience should be used as an objective measure to evaluate competency. The idea is to use a threshold of X amount of bronchoscopies after the bronchoscopist can perform unsupervised (Ernst, Silvestri, Johnstone, & American College of Chest Physicians, 2003). In line with this method, Barsuk, Cohen, Feinglass, McGaghie, and Wayne (2017) have shown that procedure experience is correlated with bronchoscopy competence. However, they discovered that the majority of senior trainees in their study performed bronchoscopy below the study's developed baseline competence. If senior trainees potentially conduct bronchoscopy below the baseline level, it is questionable whether they should assess the competence of others. All these aspects show that the apprenticeship model has several shortcomings. There is a need to discover behavioural markers of expertise that can assist in assessing competency without being subjective or resource heavy.

1.3 Motion Tracking Technologies

The flexible scope is controlled with the hand. Movement of the hand in three-dimensional space leads to a corresponding action in the bronchoscope's tip. If we think of ways to reposition or move our hand, the most obvious way that comes to mind is to move the wrist. Alternatively, we can use our lower and upper arms to relocate the hand and the bronchoscope. Finally, turning the upper

body or even switching our position by walking could be a valid option. Although it sounds promising that bronchoscopist have a great repertoire of movements to handle the bronchoscope, some movements are probably inefficient or even counterproductive. For instance, walking around the patient, besides being impractical due to the limited space in an operating room (Mehta, Avasarala, Deshwal, & Gildea, 2020), takes longer and requires more energy than a wrist movement (Goossens, Wybouw, Van Leeuwen, & Bonte, 2020). Wrist movements, on the other hand, come with the limitation that they cannot rotate the bronchoscope in one direction indefinitely, forcing the bronchoscopists to adapt their movement at some point (Khare, Bascom, & Higgins, 2015). Therefore, choosing the correct action partially determines how successfully and safely the operator can navigate the lung segments and will likely improve with experience (Khare et al., 2015).

For this reason, motion analysis technology is a logical candidate for identifying expert-level bronchoscopy skills. Motion analysis technology would allow for collecting various kinds of data, such as the speed or direction of movement. Research using motion analysis has already demonstrated that experienced bronchoscopists are likelier to keep the flexible scope in a straight vertical line (Colella et al., 2015). Although these observations help to gain insights into how experts utilize their experience, the performance measure used by Colella et al. (2015) is hardly enough to discriminate between poor, sufficient or excellent bronchoscopy navigation. Keeping the flexible scope straight is only one of many potential performance measures. Knowing the correct arm placement, the movement of the hand, or the speed of the movement, to name a few, might be necessary to comprehend how experts carry out a complication-free bronchoscopy.

In general, motion analysis technology should identify the essential movements. Simulated bronchoscopy is not an exact replication of actual bronchoscopy, and there will be qualitative differences between the two. Some participants might perform better on a simulator; others might think the simulator feels more like a game making it difficult to associate it with real bronchoscopy. Nevertheless, the two have strong similarities, which means they have a common set of movements that are key for a smooth performance. The goal of motion analysis technology is to discover these critical movements.

Although it is not within the scope of this study, we could use the insights gained from the motion technology to develop a threshold score in the future. In a study by Cold et al. (2021), they applied an EMG technology (measuring muscle activation) to assess the motor skill performance of novices, intermediates, and expert bronchoscopists. Using the data obtained from the EMG technology, they developed a threshold score, which effectively separated the novices and intermediates from the experts. Hence, this score could serve as an objective assessment that beginners can actively work towards until they are ready to operate on actual patients (Cold et al., 2021).

1.4 Learning Motor Skills

Learning to operate and handle the bronchoscope requires hours of dedication and repetition. Learning happens in three sequential phases within the context of minimally invasive surgery (MIS) (Ericsson, 2004). In the first phase, the unconscious and conscious incompetence, the learner needs to utilise a significant number of cognitive resources to avoid making mistakes while being partially unaware of what of their performance has caused these mistakes. Moreover, conscious incompetence involves getting a grasp of the task or activity at hand before being able to improve one's performance. With more repetition, the learner reduces gross mistakes to a minimum, and the performance becomes more refined despite needing fewer cognitive resources. This is the second phase and is often termed conscious competence. The final phase, unconscious competence, states that the learner can perform the activity completely automatically, investigating only a minimum of cognitive resources (Ericsson, 2004). The final phase also defines the performance limit as the learner typically does not improve anymore and revolves around this limit.

While the theory of Ericsson (2004) can explain how learning proceeds with repetition and experience, it has the issue of dividing the trainee into three distinct groups. Expertise is a continuous phenomenon in the sense that an individual does not abruptly rise to the next level but gradually improves with each repetition. Besides, there will always be differences in competency within groups (say intermediates) next to the between-group differences. A learning theory that takes into account the continuous nature of expertise is the tweak-finder model developed by Schmettow (in prep., ch 9.1).

The tweak-finder model describes learning a skill as a series of finding tweaks. Everyone has a distinct pool of tweaks depending on the amount of skill the individual already possesses (amplitude). Beginning to learn a skill corresponds to a large collection of tweaks. With each repetition, the finite pool of tweaks becomes smaller. Finding a tweak always has the same probability regardless of the current pool of tweaks. Despite the probability always being equal, the chance of finding a tweak reduces each time the pool gets smaller. In other words, enhancing your skills (finding a tweak) is relatively straightforward when many aspects can be improved. Conversely, people who have perfected their abilities will have difficulty improving their skills and finding potential tweaks. When the pool of tweaks is drained, we speak of achieving maximum performance (asymptote). Since discovering a tweak becomes more difficult with a decreasing pool, learning takes an exponential shape (*Figure 1*). Finally, finding a tweak is irreversible because an acquired skill cannot be unlearned again. Since bronchoscopists vary in their experience and the number of conducted bronchoscopies, the tweak-finder model can pinpoint the expertise more accurately than the theory of Ericsson (2004).

Based on the theory of Ericsson (2004) and Schmettow (in prep., ch 9.1), we can construct quantitative assumptions predicting how the groups will perform. The novices begin with a large pool of tweaks. Consequently, they will make gross errors as they will likely need time to understand the

task first. However, after the novices have grasped the task, the tweak-finder model predicts that they will show the most potent skill acquisition due to the greater number of undiscovered tweaks compared to the intermediates and experts. The intermediates make fewer mistakes than the novices and need considerably less time to complete the activity. They have discovered some tweaks that help them to rely on their skills instead of purely using cognitive resources. Finally, the experts have automated their performance, meaning they should make almost no mistakes while finishing the activity the quickest. Their pool of tweaks should be close to empty, and their learning should come to hold. These predictions are merely approximations, and it could be the case that, for instance, intermediates perform on an expert level and vice versa.

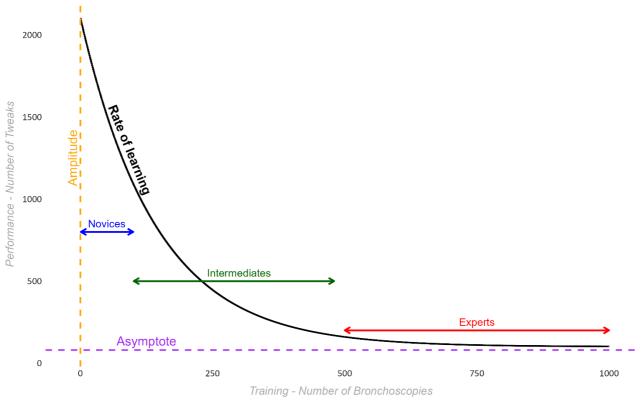


Figure 1. The Tweak-Finder Model based on Schmettow (in prep., ch 9.1). The arrows present a rough approximation of the training the groups have had in the past and how their amplitude and learning rate might vary accordingly.

Although automated performance is the supreme goal of learning in many disciplines and activities, including bronchoscopy, it could turn out as a problem for the experts within the scope of this study (Besnard & Cacitti, 2005). The experts have learned bronchoscopy skills by operating on actual patients, and in this study, they must perform the tasks on a simulator. In case that simulated bronchoscopy varies slightly from real bronchoscopy, the automated skills the experts have acquired might make them blind to these differences. The intermediates probably perform bronchoscopy more

consciously. They will notice that simulated bronchoscopy deviates from actual bronchoscopy and can adapt their movement to these differences. In other words, if simulated bronchoscopy differs from actual bronchoscopy, but the experts assume it does not, they might fall victim to negative transfer impeding their performance (Besnard & Cacitti, 2005).

1.5 The Present Study

The main goal of this study is two-fold. The first goal is to identify behavioural markers of bronchoscopy expertise that can reliably distinguish the motor skill performance of novice, intermediate, and expert bronchoscopists. To come up with said behavioural characteristics, motion analysis technology is utilised, which keeps track of the velocity, acceleration, and direction of the hand and arm movement. We expect that the experts will have the highest acceleration and velocity as they have automated their performance. Accordingly, they will take the least time to complete the bronchoscopy procedure and minimize the number of errors. The intermediates follow right after. Since we hypothesize that they lack the automatization of the experts, they will be slower, need more time and are more error-prone. Finally, the prediction for the novices is that they will prioritize error avoidance. Their movement should be characterised by stiffness due to low acceleration. Ultimately, they will still make more mistakes than the other two groups and require the most time to finish.

The second aim is to estimate a learning curve model using these behavioural markers and the tweak-finder model (Schmettow, in prep., ch 9.1). The learning curves would then allow pinpointing the current skill level of the trainee as well as the training required to reach the intermediate or expert level. Previous research has already applied learning curve models using the tweak-finder model to predict skill possession and acquisition of novice trainees in a bronchoscopy (Küpper, 2018; Westerhof, 2018) and a laparoscopy setting (Arendt, 2017; Kaschub, 2016; Weimer, 2019). Outside of the medical domain, Voskes (2022) has demonstrated that the tweak-finder model can successfully model the learning curves of inexperienced and experienced drivers in a driving simulator using completion time and the number of errors as outcome measures. Likewise, this study aims to model individual learning curves separately for each proficiency using the same outcome measures.

1.6 Ethical Approval

Ethical approval for this study was granted by the BMS ethical committee / Domain Humanities & Social Science (*Appendix A*).

2. Methods

2.1 Design

This study employed a between-subjects design comparing the performance of participants segregated into three different groups: Novices, intermediates, and experts. Each participant performed two common bronchoscopy tasks on a simulator, and their performance level and movement parameters were extracted.

2.2 Participants

In total, 30 participants were recruited for this study. 13 of the 30 participants were novices, 9 were intermediates, and 8 were experts. We classified the participants into one of the three proficiency groups based on how many previous bronchoscopies they had performed on patients. The novices had no prior experience with bronchoscopy, meaning they had never conducted any bronchoscopies. The intermediates performed between 5 and 100 bronchoscopies, and the experts performed more than 500. However, some participants executed between 100 and 500 bronchoscopies. Due to data scarcity, these participants were not excluded and have been categorised as intermediates. None of the novices had any experience with simulated bronchoscopy. The intermediates were mainly all familiar with the simulator, and the experts reported having some experience with simulated bronchoscopy.

A short look at the demographic data reveals that with 23 participants, the majority is of Dutch nationality, 5 participants are German, and two indicated another nationality. In total, 18 participants were female (Intermediates = 6, Experts = 3, Novices = 9), 12 participants were male (Intermediates = 3, Experts = 5, Novices = 3). The novices have a mean age of 23.1 years (SD = 2.58). They have been mainly enrolled through the recruitment system of the University of Twente (SONA). The intermediates have a mean age of 28.3 years (SD = 4.64), and the experts are older on average, with an age of 45.6 years (SD = 12). The intermediates and experts have been recruited through connections to hospitals stationed in different parts of the Netherlands. Besides, the participants indicated which hand they used to conduct bronchoscopy. Twenty-two participants stated they use the right hand (or prefer the right hand in the case of the novices), and the remaining 8 used the left hand.

2.3 Bronchoscopy Simulator - GI-BRONCH MentorTM

The Gi-BRONCH *Mentor*TM bronchoscopy simulator belongs to the family of medical simulators developed by Simbionix ("GI Bronch Mentor - Indizium", 2022). The simulator integrates simple, basic tasks and tasks representing more complex clinical procedures. Besides, the simulator is flexible regarding the working position allowing the operator to reposition during the process. Multiple modalities of feedback are available to the operator, including haptic sensations of the scope handle and patient-related complications through the imitation of, for instance, bleeding or hypotension. The

bronchoscope's tip is equipped with a movement sensor that reveals information about the current position. This information is then used to create a 3D replication of the patient's endoscopic view. Finally, the endoscopic view is live-streamed to a 24-inch large screen. The supervisors can use the simulator to monitor the trainees through the screen and obtain performance metrics to track their progress ("GI Bronch Mentor - Indizium", 2022).



Figure 2. The GI-BRONCH Mentor[™] Simulator

2.4 Tasks

The participants performed two different tasks. The first task required the participants to follow a blue ball through a virtual, metallic-looking tube (*see Figure. 3*) until they reached the end of the tube signalised by a signal tone. The tube consists of various junctions resulting in a multitude of different paths that the ball could take. The simulator randomly chose the paths, which could not be tracked or followed up afterwards. Due to the randomisation, learning effects were not affected by participants remembering the route and repeating the same movement. If the participants got in contact with the walls of the tube mirroring the lung walls, they were notified by a loud banging noise. The simulator's performance metrics provided how often the participants hit the wall and the percentage of time they were in contact with the wall. Additionally, the time it took to complete the task was recorded.

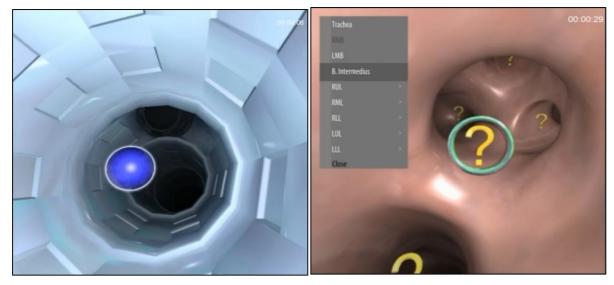


Figure 3 and 4. Illustrating task 1 and task 2, respectively.

The second task's visual outlook was more realistic to than that of an actual human lung system. This task's aim was to navigate through the whole lung system and stepwise reach the lung segments displayed in *Figure 5*.

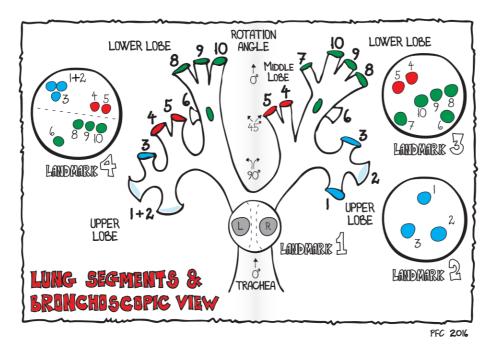


Figure 5. Illustration of the left and right lung (Clementsen, Nayahangan, & Konge, 2016). *The individual segments are highlighted by the numbers 1 to 10.*

In total, there were 18 different segments. At each segment, the participants were shown a yellow question mark. To successfully reach the segments, the participants were required to get in close range and direct their view frontally on the question mark until a green edging appeared. As this study

aimed to assess motor skills and not knowledge or memory capabilities, one of the researchers, knowledgeable about the airway system, guided the participants through the segments. Due to the task being longer and requiring more reallocations of the bronchoscope compared to the first tasks, the participants more frequently got stuck and had difficulties progressing. In case this happened, the researcher advised on how to reallocate the bronchoscope preventing the participants from getting stuck and requiring substantial time. Finally, since there was no sound signalising the end of the task, the researcher notified the participants that they were done.

2.5 Motion Analysis Technology – Xsens

The motion analysis technology of choice was the Xsens motion capture suit. The Xsens suit consists of 18 sensors placed on various body parts (XSens Inc, 2017). 11 sensors are located on the upper body, and seven are reserved for the lower body. The Xsens software, MVN analyse, allows for the specification of the relevant body dimensions giving the choice to track the whole body, the upper body, or the lower body. With the research interest in hand and arm movement, using only the upper body was sufficient. The sensors are on the hands, upper arms, lower arms, left and right shoulder, pelvis, sternum, and head. Each sensor streams the data of interest to the Awinda station, which is connected to a computer and sends the data to the MVN analyse software (XSens Inc, 2017).

Xsens uses the right-handed Cartesian coordinate system as the global direction of the segments (hand, forearm, and upper arm). In this frame, the x-axis points to the local magnetic North, the y-axis is based on the right-handed coordinate system (West), and the z-axis points up (see *Figure* 6 for a visual illustration).

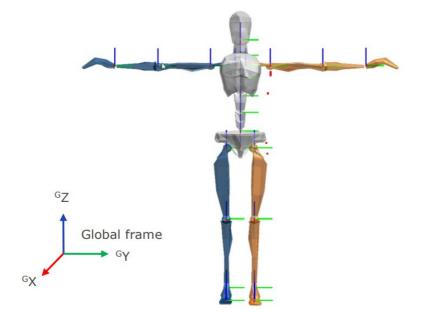


Figure (6). Global coordinates of the Xsens body segments (Xsens Inc, 2017) The x-axis is equal to red, the y-axis is green, and the z-axis is blue.

2.6 Procedure

At the start of the experiment, the participants were informed about the purpose of the study and got a short introduction to bronchoscopy and the simulator. The participants were told that they could withdraw from the experiment at any time, regardless of the reason. Following consent, the researchers put on the Xsens suit. The suit required calibration to stabilise the orientation of the sensors and establish magnetic immunity. For the calibration, the participants stood in an N-pose for a few seconds and then walked around while simultaneously moving their hands and arms.

With the motion suit ready, the participants began with the first task. The researcher shortly explained the task. The participants repeated the first task five times. However, before the first actual trial, the participants conducted a test run to get familiar with the task and handling of the bronchoscope. The researchers verbally initialised the start of the trial. The trial ended with a signal tone. In the Xsens software, the researchers highlighted the beginning and end using an event marker function. Finished with the first task, the participants were asked if they would like to take a short break before continuing with the second task in case they felt exhausted or had muscle fatigue. Since the second task partially depended on knowledge of lung anatomy, the participants were given a short walk through the anatomy and the lung segments (see *Figure 5.*). The second task consisted of three trials. During the task, the researcher, standing next to the participant observing the screen, verbally led the participants from segment to segment. Between the trials, the participants had the opportunity for a short break due to the length of the task. For this task, the researcher announced both the start and end.

2.7 Performance Measures

The performance measures stem from three different sources. First, we have the movement parameters from the Xsens motion technology. We conceptualised movement as the body segment's acceleration and velocity and measured it for the hand, lower, and upper arm. As the body's movement happens to be in three-dimensional space, it proceeds along the x, y, and z coordinates. The x, y, and z-coordinate can be further separated into movement in the negative or positive direction. In more practical terms, the movement goes from left to right, top to bottom, and forward backward. In summary, there are four movement performance measures to discriminate between proficiencies: the type of movement (acceleration vs velocity), the body segment in question, the magnitude of the movement on the x-y-z axes, and the direction on the axes (positive and negative).

Next to the movement data, the simulator provided two performance measures: The number of times the tip of the bronchoscope collided with the bronchial wall (ConWall) and the relative percentage of time that the tip was in contact with the wall (TimeWall). Contacting the wall of the simulator is regarded as an error as it could lead to complications for actual patients. Finally, the time it took the participants to complete the tasks has been collected as an outcome measure of performance (ToT). A low completion time and few to no errors are the best outcomes as it would mean that the bronchoscopist performs fast and smoothly.

2.8 The Body in Motion - Understanding Movement

In this study, movement is conceptualised as velocity and acceleration. A true understanding of these two concepts requires a deeper theoretical basis on their interplay with other constructs, including displacement, inertia, mass, and gravity (Newton, 2012). First, velocity describes the change in displacement of an object in a specified time. Displacement is the change in the position of an object. Displacement is a vector; consequently, velocity is vectorised, indicating an object's speed and direction. Acceleration is defined by the change in velocity in a given timeframe and, like velocity, designates the direction of movement. As acceleration depends on speed, acceleration is only present if there is a change in velocity (Newton, 2012).

The relation between displacement, velocity, and acceleration can be understood more clearly when we consider position as a function and velocity and acceleration as the first and second derivatives. The first derivative indicates the slope of the function; thus, velocity describes the rate at which the position changes per unit of time. Acceleration, the derivative of velocity, denotes the change of velocity over time. Another important concept is the derivative of acceleration, called jerk. It describes the change in acceleration over time. Fast uncontrolled body movements in one direction result from too much jerk that the antagonistic muscles cannot balance out in time (Sha, Patton, & Mussa-Ivaldi, 2006). To keep the jerk at a minimum, it's derivative - termed snap - needs to be equal to zero so that the acceleration remains constant or held steady to enable a smooth increase in acceleration (Eager, Pendrill, & Reistad, 2016). These two derivatives of position have not been investigated in this study but can be meaningful for interpreting the results.

When an external force acts upon an object, the change in velocity differs depending on the object's mass. Increasing mass requires more net force to reach the same acceleration. In other words, the acceleration of an object is proportional to the force operating on it and inversely proportional to its mass. This relationship is known as the Law of Inertia (Newton, 2012). The concept of inertia follows the logical conclusion that acceleration and deacceleration of the upper arm and forearm would require more force than hand movements due to the difference in mass. Force in this context is equal to muscle activity. Therefore, exaggerated movement of the upper arm and forearm would go hand in hand with higher energy demand and possibly muscle fatigue.

Another factor we must consider when inspecting the movement is the gravitational force. Gravity constantly impacts body parts with a downward pressure (Newton, 2012). As a result, movement of body parts opposing the gravitational force requires an equal or greater amount of force in the form of muscle activity. Naturally, movement towards the negative z-direction should be favoured compared to movement in the positive direction due to less reliance on muscle activity (except for the need to deaccelerate the movement). In summary, acceleration and velocity are affected by the mass of the body segment and the forces in play.

3. Data Analysis

This study aimed to find behavioural markers of expertise that can distinguish between expert, intermediate, and novice bronchoscopy skills. The next step was to estimate exponential learning curves using these markers to develop a tool that can assess the current experience and predict the training required to reach a certain skill level. However, the estimation of learning curves was unsuccessful. Therefore, the data analysis will mainly concentrate on exploring the qualitative differences between the proficiencies. Multivariate generalised linear models were used to estimate the relationship between the movement parameters and the outcome measures.

3.1. Creating the data set

Performing analysis on the Xsens data requires the data to be in an appropriate form. Therefore, the Xsens files were converted into an Excel Workbook file (.xlsx). Afterwards, a specifically developed R script shaped the Excel files into a usable data set (see *Appendix E* for the exact procedure and the R script).

The Xsens suit recorded the acceleration and velocity with 30 Hz for each combination of body segment and direction on the x-y-z axes. This means that we have numerous data points for each participant. Therefore, the values have been aggregated to obtain mean values. In other words, we calculated the average velocity and acceleration per participant, trial, task, body segment, and direction on the x-y-z axes. Moreover, we discerned between movement in the positive and negative direction on the x-y-z axes. Afterwards, the rest of the data was added to the data set, including the outcome measures and other descriptive information (dominant hand and experience with bronchoscopy simulators).

The Xsens software measures velocity and acceleration in m/s and m/s², respectively. The human body can move relatively fast, with hand movements reaching the speed of about 6 meters per second (Cieślik & Łopatka, 2022). However, the participants in this study moved with an average rate ranging from 0.001m/s to 0.06 m/s. Analysing the effect sizes of such low numbers is complex and can become tiresome, especially when the values have many decimal places. For this reason, we transformed the values to centimetres per second. In addition, when modelling acceleration and velocity as covariates, the effect of a unit increase in the cm/s⁽²⁾ range is more meaningful since the participants' speed varied only by a few cm/s.

3.2 Learning Curve Model

The mathematical formula for estimating a learning curve is the following:

 $\mu_i = exp(\beta_{Asym}) + exp(\beta_{Ampl}) \times logit^{-1} * (1 - \beta_{Ctch})^{Trials}$

This formula is based on the LACY model (Schmettow, in prep. ch 9.5.2). The LACY model consists of three non-linear parameters: The Asymptote, Amplitude and Catch rate. The asymptote describes the maximum performance that is achievable in a given task. The amplitude defines the current skill level or experience of the person at hand. The catch rate reflects the probability that the person is making learning progress depending on the number of attempts (trials) the person performed. Due to the Catch rate being a probability, its values range from 0 to 1. At the same time, the catch rate is exponentiated by the number of trials resulting in smaller learning steps with every repetition. As such, the learning curve has an exponential decrease (or increase). To properly model learning curves, there needs to be visible learning of the participants; otherwise, the LACY model cannot estimate the catch parameter accurately. Therefore, the first step of the data analysis was to analyse if the participants, especially the novices, showed a diminishing trend in the time on task and wall contacts.

3.3 Generalised Linear Regression

With the estimation of the learning curves being unsuccessful, the next step was to analyse the differences between the proficiencies. We will start by investigating the movement to see to what extent there is a contrast between the proficiencies in terms of: How fast they move the bronchoscope in general measured by their velocity (1), how much they accelerate their movement (2), which body part if any, they use predominantly (3), and in what direction they tend to move (4). Then, the focus is on inspecting the performance measures ToT, ConWall, and TimeWall (5). Finally, we will see how acceleration and velocity are associated with the performance measures (6). For the analysis, we made use of multivariate generalised linear regressions that can estimate multiple response variables at the same time.

Moreover, for each response variable, we have neglected the Gaussian distribution and selected a more appropriate distribution based on the properties of the response variables. Correspondingly, the two movement performance measures - acceleration and velocity - have been analysed with an exponentially modified gaussian distribution (Exgaussian). The Exgaussian distribution is a three-parameter distribution allowing to adjust (next to the mean) the variance and skew of the response variable accounting for overdispersion and strong skew, respectively (Schmettow, 2021). Besides, zero does not belong to its possible outcomes, as completing the tasks without performing any movement is impossible. This means that the distribution is shifted slightly to the right. A Gamma distribution would approach a normal distribution when it is moved to the right resulting in an unmodelled left skew. With the extra parameter of the Exgaussian distribution to adjust the skew, the left tail of the distribution can be modelled accurately (Schmettow, 2021).

The time on task was modelled with an Exgaussian distribution for the same reason. On the other hand, the relative time in contact with the wall can potentially reach zero. Thus, we used a Gamma distribution for this performance parameter. The count variable ConWall (number of contacts

with the wall) was modelled using the negbinomial family to account for overdispersion. Overdispersion describes the problem of a model underrepresenting the variance existent in the data due to, among other things, lacking the additional parameter to adjust the variance (Schmettow, 2021).

These performance variables have in common that they have boundaries. For instance, the number of contacts is bounded at zero since it is impossible to have a negative amount of wall contacts. Using a linear model on such a bounded response variable could theoretically lead to negative predictions, which would be impossible in our scenario. Generalised linear models combat this problem by utilising link functions that transform the bounded measures into the range of negative to positive infinity. In this study, the applied link function was the logarithm. The mean function reverses the transformation putting the data back into its original, bounded form. After the mean function has been applied (exponential function), the slope coefficients no longer have an additive effect on the intercept but are multiplicative (Schmettow, 2021).

Instead of presenting the results with the pervasively used p-values to signal significance, this study's estimated coefficients are given alongside 95% credibility intervals. These 95% CI present an interval with an upper and lower boundary of values and articulate a 95% probability that the true value is contained in this interval. The smaller this interval gets, the greater our certainty or confidence that the centre value mirrors the actual value (Schmettow, 2021).

3.3 The models

In total, three different multivariate, generalized linear regression models have been estimated. In the first model, we predicted the two response variables acceleration and velocity. The primary predictor variable for this model was proficiency. The tasks, trials, and the combination of body segments and direction were included as an interaction effect with the proficiency variable. The model looks as follows:

(Velocity|Acceleration) = Proficiency + Task*Proficiency + Trials*Proficiency + Segment-Direction*Proficiency

The task variable is a factor with two levels (Task 1 and Task 3), and trial is a numerical variable. Segment-Direction is the combination of body segments and direction. As we have three body segments (hand, forearm, and upper arm) and three directions (x-y-z), this variable consists of nine different levels.

The second model is similar to the first model with the exception that it includes a predictor (named "Sign") that lets us discern between movement that goes into the positive or negative direction on the x-y-z axes:

(Velocity|Acceleration) = Proficiency + Task*Proficiency + Trials*Proficiency + Segment-Direction*Sign*Proficiency These two models have been compared in terms of their model fit to assess whether including the Sign variable leads to better predictive accuracy.

Finally, the last multivariate model predicted the outcome measures ToT, ConWall, and TimeWall. Next to the trials and tasks, this model included acceleration and velocity as covariates. In addition, ConWall and TimeWall have been predicted by the time on task:

ToT = Proficiency + Task*Proficiency + Trial*Proficiency + Acceleration*Proficiency + Velocity*Proficiency

ConWall = Proficiency + Trial*Proficiency + ToT*Proficiency Acceleration*Proficiency + Velocity*Proficiency

TimeWall = Proficiency + Task*Proficiency + Trial*Proficiency + ToT*Proficiency + Acceleration*Proficiency + Velocity*Proficiency

In this model, velocity and acceleration have been averaged over the body segment and the direction, meaning that we have one value representing all nine levels. Besides, we centred acceleration and velocity at the population's mean.

4. Results

4.1 Learning Curves

Before calculating the more complex LACY learning curve model, it is crucial to investigate if the participants showed signs of learning in the first place. The spaghetti plot in *Figure 7* illustrates how the time on task varies throughout the trials for each participant. When we focus on the novices, we see that their time on task increases and decreases during the first task without any apparent pattern. One of the LACY learning curve model prerequisites is continuous learning, albeit with minor fluctuations. Not a single participant continuously improved their time on task from trial to trial. However, when we focus on the difference between the first and the last trial, the novices showed signs of learning after all. In the spaghetti plot, participants for whom the time on task was greater in the last trial than in the first trial are marked in grey. Hence, under this aspect, we can see that most novices report a decrease in time on task.

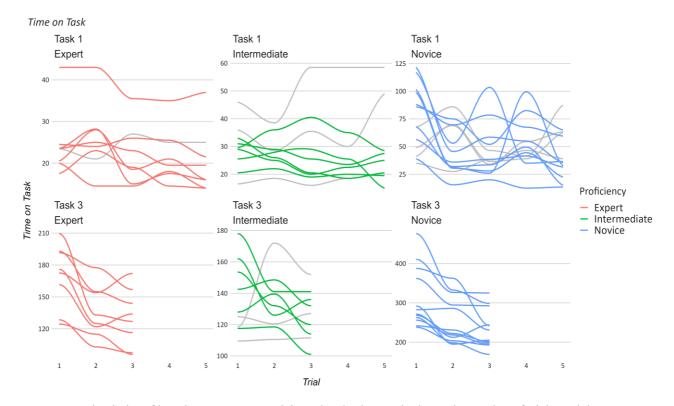


Figure 7. Spaghetti plot of learning curves on participant level. The x-axis shows the number of trials, and the y-axis the time on task in seconds. Grey-coloured curves indicate participants who took longer to complete the tasks on the last trial than on the first. Task 3 consisted of only three repetitions, which explains the abrupt ends of the curves. Note: The y-axes are rescaled based on the range of values of the respective groups.

Despite the intermediates and experts having slightly less fluctuating curves than the novices, they also do not continuously lower their ToT with each trial. The lack of constantly falling curves of

experts and intermediates can potentially be explained by the fact that they have reached their asymptote while having minor deviations in their performance. The observation that the experts and intermediates start with a lower time on task than the novices supports this explanation. If the time on task is short, to begin with, it should be much harder to improve it steadily. Although these two groups might be close to their asymptote, most experts and intermediates improved their time on task if we only consider the difference between the first and last trial.

The second task (Task 3) does not deviate much from the first task. Once again, there are small fluctuations from trial one up to trial three, but if we only look at the first and last trial, almost everyone - except for three intermediates – notes a decrease in completion time. Unfortunately, the second task consisted of merely three repetitions making it challenging to assess whether the ToT would further increase, decrease, or stagnate.

The performance measure - the number of contacts with the walls - reveals a similar picture $(Figure \ 8)$. The novices did not demonstrate clear exponential learning. The intermediates and experts are close to the maximum performance once again, with most of them having three wall contacts or less for each trial. Finally, as highlighted by the grey-coloured curves, most participants end up with fewer wall contacts at the end of the experiment compared to the beginning.

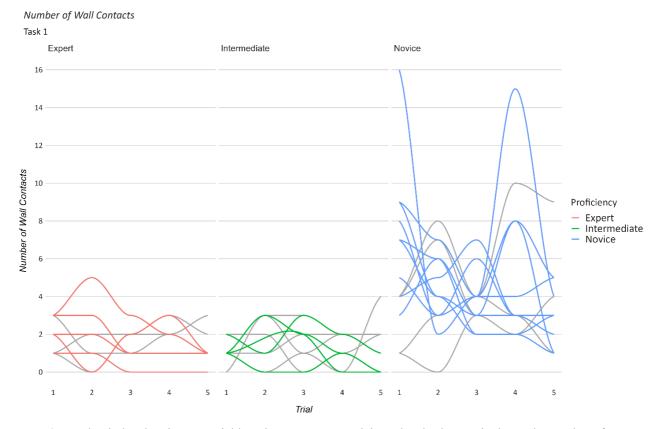


Figure 8. Spaghetti plot showing potential learning curves on participant level. The x-axis shows the number of trials, and the y-axis the number of contacts with the wall. Grey-coloured curves indicate that the participant had a higher time on task on the last trial than on the first. The plot does not include task 3 because the simulator did not record the number of wall collisions for this task.

Despite there being no learning curves on participant level, we can look at the learning effect on population level for Task 1 (*Figure 9*) to gather reassurance that exponential learning did not occur. (Task 3 was not included on population level as we lack the information about the number of wall contacts). For the most part, the curvature of the novices decreases with a small peak again at trial 4. On the other hand, the intermediates and experts have roughly the same performance measure for every attempt when averaging over participants, which makes sense if we assume that they have almost reached their asymptote. All in all, we can see that the estimation of learning curves was unsuccessful due to no sign of continuous learning for any proficiency. Nevertheless, some form of learning happened between the first and last trial, even for the experts and intermediates. Thus, a more continuous learning effect might have been discovered with more repetitions.

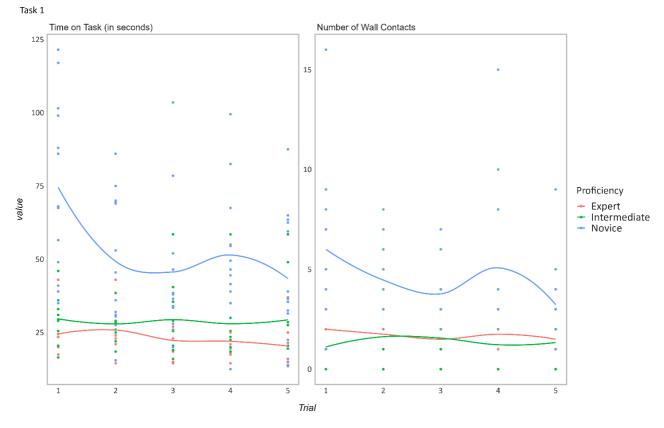


Figure 9. Raw learning curves on population level for task 1. The x-axis presents the number of trials. The y-axis shows the ToT in seconds or the number of contacts with the wall.

4.2 Distribution of Movement Parameter

Before turning to the regression analysis results, we inspect the distribution of the raw movement data. The violin plots in *Figure 10* highlight the distribution of the acceleration and velocity separately for each body position and direction. Most violin plots have a greater thickness at the bottom spectrum and get thinner towards the upper end. As such, the distribution demonstrates that the data is highly skewed to the right with a long right tail. Thus, it makes sense to use an Exgaussian

distribution that can account for this long right tail. Besides, we can already observe that the experts and intermediates have a more pronounced right skew than the novices meaning that they have performed fast movements more frequently than the novices. On the other hand, beginners have the most significant distribution at the lower end of the acceleration and velocity scale. The hand has the highest acceleration and velocity in the body segments, followed by the forearm and the upper arm. Based on this plot alone, it is not readily apparent if there are any directions that the participants predominantly utilised.

If we take a more general stance, we can observe that acceleration has far higher values than velocity, as velocity does not even exceed six cm/s. Acceleration consistently exceeds velocity for a specific period when an object is set in motion. For instance, when a bronchoscopist abruptly starts accelerating her hand with 40 cm/s², then within this one-second velocity is below the 40 cm/s threshold. After one second, the speed is greater than 40 cm/s and beats the acceleration. The fact that the average acceleration is greater than the average velocity shows that bronchoscopy involves constant acceleration and deacceleration rather than a steady pace.

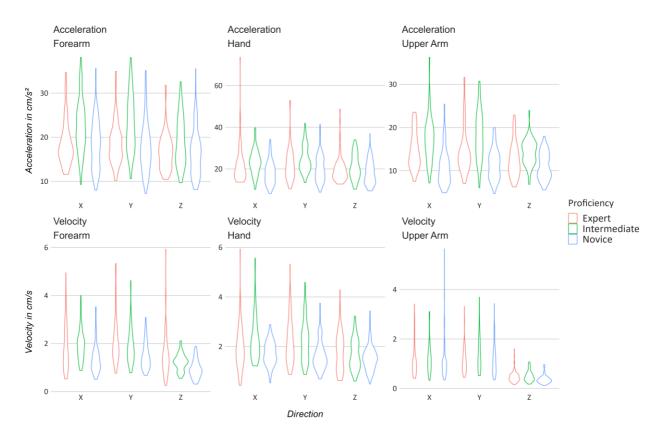


Figure 10. Violin plot: showing the distribution of the velocity and acceleration separately for the body part and direction. The x-axis showcases the direction of the body segments on the x-y-z axes. The y-axis presents the velocity and acceleration in cm/s and cm/s², respectively.

4.3 Generalised Linear Regression

4.3.1 Regression Results – Movement

We will start our analysis with the first generalised linear regression model (as described in Section 3.3 – The models) predicting the two movement parameters, velocity and acceleration. *Tables 1 to 3* present the results of this regression analysis (acceleration), including the centre values and the 95% certainty intervals.

Starting with the acceleration, the experts have an estimated average acceleration of 19.39 [18.57, 20.19] cm/s². The credibility of this estimate is decent, with the lower and upper confidence interval roughly in the range of 1/20 of the centre estimate. The intermediates accelerated with 21.14 [19.78, 22.53] cm/s², which is 1.75 cm/s² faster than the experts' acceleration. The novices are the slowest group. They report an acceleration of 17.24 [16.00, 18.49] cm/s² making them 2.15 cm/s² slower than the experts.

The intercepts only represent the estimates for the movement of the hand in the X direction, as this combination of body segment and direction was chosen as the reference group. However, it is a reoccurring scheme for almost all the other combinations, too, that the intermediates have the highest acceleration and velocity, the novices have the lowest, and the experts are somewhere in-between. There are a few exceptions to this rule, where beginners, for instance, have a greater velocity than the experts. We will inspect this pattern more thoroughly later.

Next, we can look at the trial's effect on the movement data. The centre estimates show that with each trial, acceleration increases by a small amount ranging from 0.10 to 0.42, depending on proficiency. The novices have the lowest gain per trial, and the 95% confidence interval even suggests the possibility that each trial reduces their acceleration. Switching from the first to the second task, there is a decrease in acceleration of different magnitudes for each proficiency.

		95% Confidence Interv	
ToT - Experts	Effect Estimate	Lower	Upper
Intercept	19.71	18.73	20.68
Trial	0.32	0.16	0.49
Task	-0.34	-0.78	0.09

Table 1. Acceleration – Population Level Estimates - Experts

Table 2. Acceleration –	Population Level Estimates	- Intermediates

		95% Confidence Interval	
ToT - Intermediates	Effect Estimate	Lower	Upper
Intercept	21.14	19.78	22.53
Trial	0.42	0.19	0.64
Task	-1.02	-1.63	-0.41

		95% Confidence Interval	
ToT - Novices	Effect Estimate	Lower	Upper
Intercept	17.24	16.00	18.49
Trial	0.10	-0.12	0.31
Task	-0.86	-1.42	-0.30

Table 3. Acceleration – Population Level Estimates - Novices

Tables 4 to 6 contain the predictions for velocity. In comparison to the acceleration, the novices have with 1.70 [1.45, 1.95] cm/s, a greater velocity than the experts (1.61 [1.50, 1.72] cm/s). But remember that the intercept only presents the hand in the X-direction. In short, we will see that this observation is only an exception. The intermediates have an average velocity of 2.11 [1.86, 2.37] cm/s, which makes them almost $\frac{1}{4}$ faster than the experts.

With each trial, the centre estimates predict that the velocity of each group inflates by a small amount. However, it cannot be excluded that the intermediates have a negative effect (0.01 [-0.02, 0.04] cm/s). The second task (Task 3) required an overall lower acceleration but higher velocity than the first. The experts' and intermediates' velocity rise by a factor of 0.12 cm/s and 0.08 cm/s, respectively. Although the novices have only a minimal negative effect, their lower and upper confidence interval allows for a strong positive or negative impact.

		95% Confidence Interval	
Velocity - Experts	Effect Estimate	Lower	Upper
Intercept	1.61	1.50	1.72
Trial	0.03	0.01	0.05
Task	0.12	0.06	0.18

Table 5. Velocity – Population Level Estimates - Intermediates

		95% Confidence Interval	
Velocity - Intermediates	Effect Estimate	Lower	Upper
Intercept	2.11	1.86	2.37
Trial	0.01	-0.02	0.04
Task	0.08	0.01	0.16

Table 6. Velocity - Population Level Estimates - Novices

		95% Confidence Interval	
Velocity - Novices	Effect Estimate	Lower	Upper
Intercept	1.70	1.45	1.95
Trial	0.02	0.00	0.05
Task	-0.0003	-0.07	0.07

Body Segments and Direction

In order to get an understanding of what truly sets apart (or not) the experts from the intermediates and novices, we need information on the extent to which they utilise their hand, forearm, and upper arm, as well as in what direction they predominantly move these body segments. *Figure 11* shows a conditional plot investigating the interaction between the body segments and direction separately for each group and measure (acceleration and velocity). In general, a conditional plot can effectively showcase differences between groups. If the lines of the conditional plot proceed in parallel, the effect is constant between groups, although it might be shifted upward or downward. With rising unevenness, the contrasts between groups grow simultaneously. We can derive multiple observations from this plot.

Overall, the body part with the greatest amount of movement is the hand, followed by the forearm and the upper arm in last place. Furthermore, the intermediates have the fastest movement regardless of the type of measure, the body part, or the direction, with only one exception: The velocity of the upper arm in the Y direction. When comparing the intermediates and experts, there is a reversed direction for the hand and forearm movement: The intermediates have the highest **acceleration** in the Y direction, while they have more **velocity** in the X direction. Conversely, experts tend to **accelerate** their hand and forearm more in the X direction, whereas they prefer the Y direction regarding **velocity**. Thus, the most notable contrast between experts and intermediates is the hand's acceleration and velocity. These differences are substantial, with the intermediates having about 16 % more **acceleration** in the Y direction and 24% more **velocity** in the X direction than the experts.

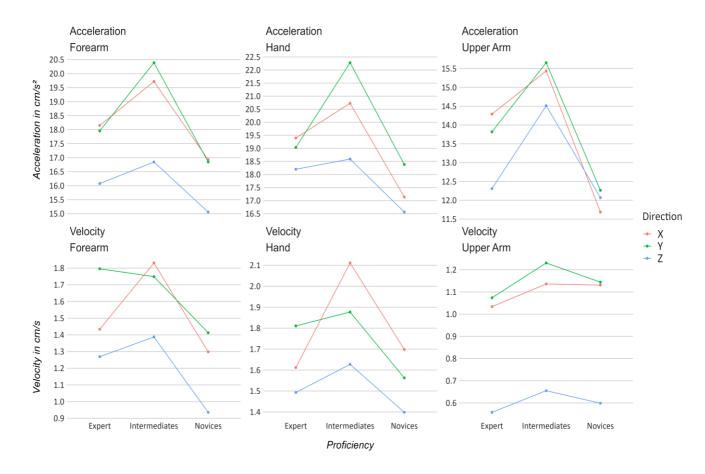


Figure 11. Conditional plot showing the difference in acceleration and velocity based on the body part and direction. The x-axis is equal to the proficiency and the y-axis shows the velocity and acceleration.

For now, we have only looked at the experts and intermediates. As aforementioned, the novices did not demonstrate an exponential learning effect. A closer look at their body movement might reveal hints at what potentially inhibited them from an apparent learning effect. Mostly, nothing is striking about their kind of movement. They almost always have the lowest values for acceleration and velocity. Exclusively the velocity of the upper arm and the hand in the X direction can compete with the experts with a slight advantage. As such, the velocity of their upper arm is disproportionally high compared to the acceleration of the upper arm and all the other body segments

Difference between positive and negative direction

Gravity is a downwards-directed force that is constantly in play affecting our movement. Movement opposing gravity requires more muscle activity, and the muscles become fatigued after a while. Logically, the expectation is that moving downwards (negative z-axis) should be preferred compared to moving upwards (positive z-axis). In general, there might be discrepancies between the positive and negative directions that could explain why one group performed better than the others. A separate analysis was run that further divided the axes (x,y,z) into positive and negative directed movement (called "Sign"). *Figure 12* highlights the amount of difference between the positive and negative values.

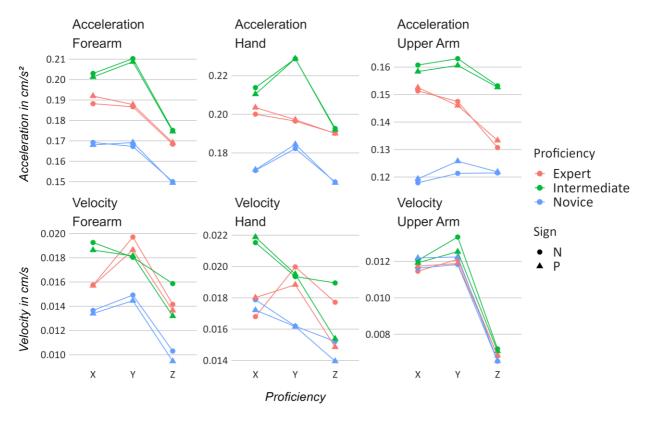


Figure 12. Comparison of movement between the positive and negative direction. The x-axis is equal to the proficiency and the y-axis shows the velocity and acceleration. The circles represent acceleration/velocity in the negative direction (N) and the triangles stand for the positive direction (P).

The more these two points diverge, the greater the difference. Predominantly, the negative and positive values converge or show only minimal dissimilarity. The only exception to this rule is the velocity of the hand and forearm on the z-axis. The velocity of the hand was faster when it was going in the negative z-direction. This effect was not recorded for the novices. Interestingly, the acceleration of the hand on the z-axis appears to be the same for positive and negative movement.

Next, we used the LOO Information Criterion to compare the model fit, once with the Sign predictor and once without. The results are displayed in *Table 7-8*. Regarding acceleration, including the Sign predictor does not lead to a better model fit. Modelling velocity with the Sign predictor results in a slightly better model fit, likely because it can render the previously identified 'negative' movement of the hand and forearm more accurately. The final regression we used to model velocity does not contain the Sign predictor since the information criteria do not differ much (Diff IC = 10.09). Nevertheless, the observation that the velocity of the hand is greater on the negative than on the positive z-axis should be kept in mind.

Model	IC	Estimate	SE	Diff IC
Without Sign	looic	-14176	110	0.00
With Sign	looic	-14122	110	53.81

Table 7. Model fit of Acceleration with and without Sign as Predictor

Table 8. Model fit of Velocity with and without Sign as Predictor

Model	IC	Estimate	SE	Diff IC
With Sign	looic	-32482	110	0.00
Without Sign	looic	-32472	110	10.09

4.3.2 Results - Performance Measures

Thus far, we have analysed the regression results regarding the movement parameter. The performance parameters measuring the time on task and the number of errors have not received any attention yet. *Tables 9-11* depict the regression results for the time on task, *12-14* the number of wall contacts (ConWall), and tables *15-17* the relative time in touch with the wall (TimeWall).

Time on Task

The centre estimates state that the experts took about 44 [28.91, 56.96] seconds to complete task 1. The intermediates are approximately equal with roughly 47 [29.79, 65.20] seconds, a rise of 3 seconds in contrast to the experts. As expected, the novices spent the most time on task 1, with an estimated 64 [45.78, 84.64] seconds, 20 seconds more than the experts. In general, the credibility intervals for the intercepts are moderate, as they are in the range of 1/3 of the centre estimate. The experts (-1.96) and intermediates (-0.97) do not improve much with each trial because they may have reached their asymptote. On the other hand, the novices could improve significantly, completing the task by 6 [-

10.86, -1.61] seconds less per trial. This observation reflects the insights we gained from the learning curves demonstrating that the novices managed to reduce their completion time over the course of the five trials (three for Task 3). Overall, the task slope effect tells us that the second task was more time-consuming. Besides, the experts took longer than the intermediates to complete the second task.

		95% Confidence Interval	
ToT - Experts	Effect Estimate	Lower	Upper
Intercept	43.90	28.91	56.96
Trial	-1.96	-5.23	1.12
Task	100.78	89.95	111.88
Acceleration	-0.69	-2.21	0.75
Velocity	1.04	-11.53	11.43

Table 9. Time on Task – Population Level Estimates - Experts

Table 10. Time on Task – Population Level Estimates - Intermediates

		95% Confidence Interval	
ToT- Intermediates	Effect Estimate	Lower	Upper
Intercept	47.15	29.79	65.20
Trial	-0.97	-5.19	3.22
Task	93.59	80.60	106.23
Acceleration	-0.56	-2.32	1.23
Velocity	2.82	-14.07	19.59

Table 11. Time on	Task – Population I	Level Estimates	- Novices
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		95% Confidence Interval	
ToT - Novices	Effect Estimate	Lower	Upper
Intercept	64.48	45.78	84.64
Trial	-6.08	-10.86	-1.61
Task	169.5914	156.4783	182.15
Acceleration	0.41	-1.26	2.16
Velocity	-10.75	-26.48	5.58

Number of contacts with the bronchial wall

The estimates of the ConWall parameter reveal that the experts have an average of 1.67 [1.03, 3.37] wall contacts at trial one and ToT = 0. The intermediates are slightly more error-prone with 1.87 [0.96, 5.21] wall contacts, and the novices collided with the wall about four times [1.66, 13.34] at trial 1. However, the certainty of these effects is sparse because the confidence intervals vary considerably. As the values for the ConWall parameter have been log-transformed, the slope effects are no longer additive but multiplicative. The trials have a similar impact on the wall contacts as they have on the completion time: Per trial, the wall collisions of the experts and intermediates remain almost the same with a slight diminishing trend. The novices reduce their error rate by about 6% with each trial. These effects must be taken with a grain of salt, as the confidence intervals allow for significantly smaller or greater effects. Finally, the contacts with the wall have been predicted by the ToT. Essentially, this slope effect explains how much the wall contacts amplify when the ToT rises by one second. The

experts have the highest increase, with an estimated 4% [1.01, 1.07] more contacts per second. In contrast, the intermediates and novices have an estimated increase of only 1% per second.

		95% Confidence Interval	
ConWall - Experts	Effect Estimate	Lower	Upper
Intercept	1.67	1.03	3.37
Trial	0.99	0.83	1.19
ТоТ	1.04	1.00	1.08
Acceleration	1.01	0.93	1.09
Velocity	0.90	0.46	1.65

Table 12. ConWall - Population Level Estimates - Experts

Table 13. ConWall - Population Level Estimates - Intermediates

		95% Confidence Interval	
ConWall - Intermediates	Effect Estimate	Lower	Upper
Intercept	1.87	0.96	5.21
Trial	0.99	0.75	1.29
ТоТ	1.01	0.97	1.06
Acceleration	1.01	0.92	1.12
Velocity	1.02	0.41	2.59

		95% Confidence Interval	
ConWall - Novices	Effect Estimate	Lower	Upper
Intercept	4.17	1.66	13.34
Trial	0.94	0.76	1.15
ТоТ	1.01	0.97	1.05
Acceleration	1.04	0.96	1.13
Velocity	1.04	0.51	2.20

Table 14. ConWall - Population Level Estimates - Novices

Time in contact with the bronchial wall

At last, the relative time that the participants were in contact with the wall has been modelled. For the first task and trial 1, the experts touched the walls for about 18% [6.43, 19.43] of the total time. The intermediates are more thorough and touch the wall only 8.5% of the time. At last, the novices have the highest estimate with 18.72% [8.98, 38.84], an inflation of 80% [0.78, 3.54] compared to the experts. The trials have a mediocre effect ranging from -2% (intermediates) to no effect (novices) to a 3% increase (experts). Nonetheless, the trial parameter has relatively large confidence intervals allowing for both strong negative and positive effects.

The effects of ToT are mostly neglectable since they approach a value of 1. In the language of multiplication, this means that these parameters have close to no impact. The ToT slope has such a small effect size because the variance contributed by the ToT parameter is likely explained by the task parameter. As can be seen in *Tables 7-9*, completing the second task took the participants significantly longer on average. Thus, it is likely that the variance explained by the ToT is rendered

by the task parameter instead. It seems that touching the wall is more common in the second task, as every group reported a significant increase.

		95% Confidence Interval	
TimeWall - Experts	Effect Estimate	Lower	Upper
Intercept	10.88	6.43	19.43
Trial	0.98	0.85	1.13
Task	4.14	1.17	14.30
ТоТ	1.00	0.99	1.01
Acceleration	1.02	0.96	1.09
Velocity	0.92	0.57	1.53

Table 15. TimeWall - Population Level Estimates - Experts

Table 16. TimeWall – Population Level Estimates - Intermediates

		95% Confidence Interval	
TimeWall - Intermediates	Effect Estimate	Lower	Upper
Intercept	8.49	4.16	17.74
Trial	1.03	0.85	1.26
Task	8.29	1.38	53.11
ТоТ	1.00	0.98	1.01
Acceleration	1.01	0.94	1.09
Velocity	0.70	0.35	1.37

Table 17. TimeWall - Population Level Estimates - Novices

		95% Confidence Interval	
TimeWall - Novices	Effect Estimate	Lower	Upper
Intercept	18.72	8.98	38.84
Trial	1.00	0.83	1.19
Task	2.93	0.69	13.09
ТоТ	1.00	0.99	1.01
Acceleration	1.02	0.95	1.10
Velocity	1.04	0.53	2.01

Relation between completion time and performance error

As illustrated by *Figure 13*, the experts have the lowest ToT and the most minor contact with the walls at the first trial and task 1. At first glance, it might appear that the experts are both: more efficient due to their low completion time and more thorough since they make fewer mistakes compared to the intermediates. However, the contacts with walls are estimated for a ToT of 0. Inspecting the results when the ToT is located at zero seconds is not meaningful and, strictly speaking, would be impossible. That is why we need to observe how the wall contacts change when the ToT is centred at a reasonable amount. Based on *Figure 14*, we can tell that with each second passing, the experts touch the walls more often on average.

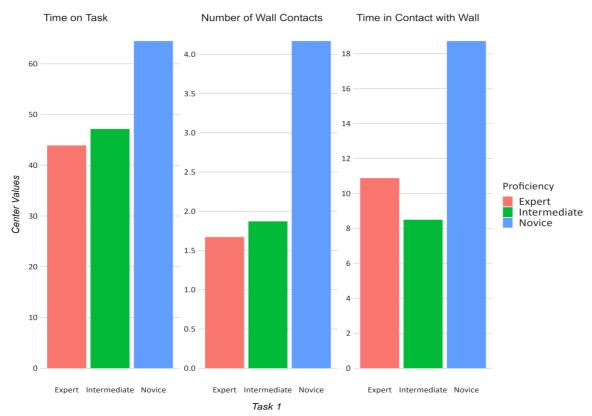


Figure 13. Differences in time on task, number of contacts with the wall, and the time in contact with the wall at Trial 1 and ToT = 0 (only applies to ConWall and TimeWall)

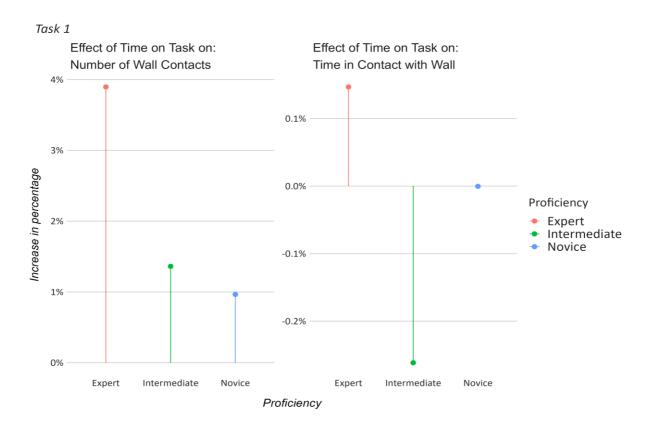
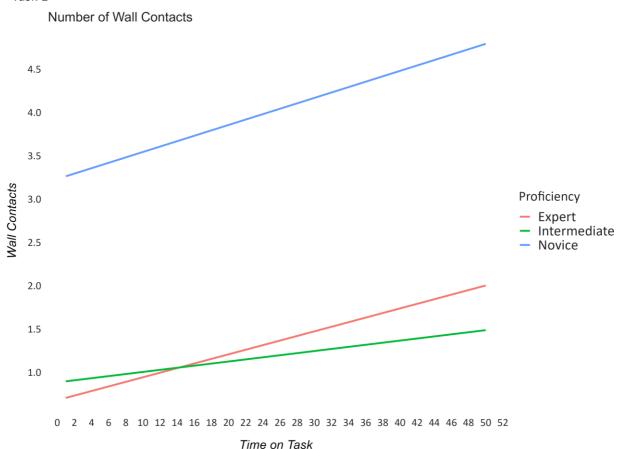


Figure 14. The percentual increase of wall contacts and time in contact with the wall per second.

To get a complete picture, we must look at how the wall contacts differ after some time has passed. *Figure* 15 demonstrates the relationship between the time on task and the number of wall contacts for each proficiency. Once again, we can see that the experts have the lowest wall contacts at zero seconds, but the linear relationship between the wall contacts and the completion time is steeper for the experts. In other words, with each second passing, their number of wall contacts increases more than those of the intermediates. After 15 seconds, the experts overtake the intermediates in the number of wall collisions. The lowest recorded value for performing the first bronchoscopy task was 18 seconds making the intermediates less error-prone than the experts at Task 1.



Task 1

Figure 15. Relationship between time on task and the number of wall contacts. The x-axis presents the completion time and the y-axis the number of wall contacts.

The parameter measuring the percentual time in contact with the wall reveals a somewhat different picture. At trial 1, the experts already had a value of 11% in contrast to the intermediates, who touched the wall 8% of the time (*Figure 13*). In addition, with each second passing, the intermediates make less contact with the walls, whereas the experts report an increase. This ToT slope, however, is almost mitigable due to its effect size. Directly interpreting these results by saying that the intermediates have touched the wall less than the experts is complicated since the TimeWall

parameter is conditional on the overall completion time. Imagine that the ToT decreases from the first to the second trial, but the **absolute** time spent in contact with the lung wall remains the same. In this case, the TimeWall parameter would indicate that the bronchial wall was touched longer in the second than in the first trial, although it was the same amount in total numbers.

Considering that the experts have a lower completion time than the intermediates, the total number of seconds they touch the wall could be lower. Dividing the ToT by the TimeWall, we get the absolute number of seconds. *Figure 16* shows that after trial 3, the experts scored lower on the total number of seconds touching the wall.

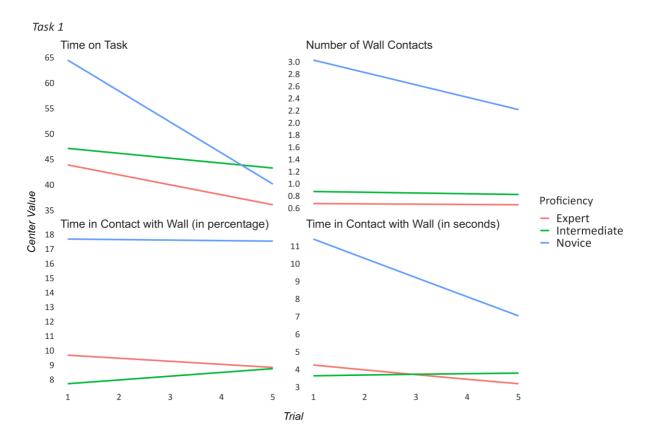


Figure 16. Relationship between the trials and the performance measures. The x-axis presents the trials, and the y-axis the number of wall contacts. SecondsWall represents the total number of seconds the participants were in contact with the wall.

Relation between movement parameter and outcome measure

The final aspect we need to consider is how the velocity and acceleration covariates are associated with our outcome measures. By investigating how the outcome measures change when acceleration or velocity increases by a certain amount, we can determine the groups' priorities in conducting flexible bronchoscopy. For example, suppose high acceleration of one group is associated with many errors. In that case, we could argue that this group will try to keep their acceleration at a minimum and, thus, refrain from making mistakes. *Figure 17* demonstrates the relationship between the outcome measures and the movement parameter separated by proficiency. Acceleration and velocity have been

centred so that their baseline values represent the mean of the respective group. The first notable pattern is that with a one-unit increase in acceleration, the novices take longer to complete the tasks and make more mistakes. Hence, novice bronchoscopists do not profit from heightening their acceleration. On the other hand, the experts and intermediates can complete the task faster when their acceleration is higher than average, but at the same time, they will make slightly more mistakes (ConWall).

The association is reversed for velocity. If velocity rises by one unit, the novices drastically reduce their time on task by about 10 seconds. We have seen earlier that the participants moved with much greater acceleration than velocity. A unit increase in acceleration is achieved more effortlessly than an increase in velocity if acceleration is much higher to begin with and varies more. Based on this observation alone, we cannot argue that velocity is more important in reducing the completion time. Nonetheless, we can observe the trend that novices have lower completion times but make more mistakes the faster they move. The intermediates are well served with the average velocity as they need longer for the tasks and collide with the wall more often if they speed up. Finally, the experts make fewer mistakes when they increase their pace, but they also require slightly more time to complete the tasks.

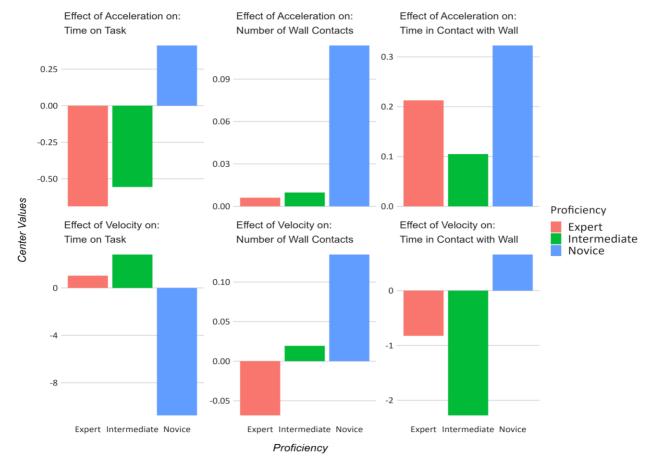


Figure 17. Bar Plot. The effect of acceleration and velocity on the outcome variable time on task, number of wall contacts and time in contact with the wall.

5. Discussion

Many different variables have been investigated during this study. The movement was measured by recording the velocity and acceleration of the hand, forearm, and upper arm on the x-y-z axes. We assessed the performance of the groups by measuring the time to complete the tasks and the number of times the participants collided with the bronchial wall. All these variables are associated with each other, and explaining one requires understanding its interplay with the other variables.

We will start by exploring why there were no learning curves found on participant level. Next, we will examine why the intermediates have the highest acceleration and velocity despite requiring more time than the experts to finish the first task. In return, this means that we need clarification on how it comes that the experts have less acceleration and velocity. While the experts finish the task more quickly than the intermediates, they are slightly more error-prone. Since experts are expected to deliver the best performance, we introduce possible interpretations to justify these errors. In the end, we will make a more detailed inspection of what characterises an expert when performing bronchoscopy by identifying how they move their hand, forearm, and upper arm and in what direction. We will also try to clarify the rationale behind these movements. As an alternative, we illustrate the type of movement that defines novice performance to see how they diverge from the experts and understand what beginners might do wrong when they are introduced to bronchoscopy.

5. 1 Learning Requires More Repetition

This study aimed to find behavioural markers of expertise that can differentiate between expert, intermediate, and beginner bronchoscopy performance without relying on subjective and ambiguous assessments. With these behavioural markers, a person's skill level can be estimated with greater reliance. Ultimately, the characteristics were supposed to be used to model learning curves that can predict the skill level after X training or experience.

In short, the estimation of learning curves failed since not a single participant showed exponential learning in terms of completion time or the number of errors. A logical and straightforward explanation for this occurrence is the lack of repeated trials. The first task was repeated five times, and the second task was repeated only three times. Most of the time, five repetitions are not sufficient to reliably observe a learning effect for a multitude of reasons.

First, in the beginning, performance in MIS procedures usually varies considerably from trial to trial as the operator is required to deal with new obstacles and situations each time. For example, in the first task, the participants needed to navigate an environment of simulated lung pathways. The simulator randomly generated these pathways, and they changed each trial. Thus, some participants might have encountered a more complex environment that necessitates intricate movements at later trials, causing them to take longer or make more mistakes than in the first trials.

Learning bronchoscopy from scratch does not only consist of finding the right hand or arm movement. A beginner needs to learn how to grab the bronchoscope handler correctly, how to position their body to the patient, or needs to develop an understanding of the task in front of him. Within the first few trials, a novice will likely change their approach depending on what they think might work best, causing fluctuations in their performance.

The intermediate and expert bronchoscopists are at the other end of the spectrum. They are close to their asymptote, the maximum performance. Consequently, they cannot improve much further and demonstrate continuous learning. Despite their experience, experts and intermediates slightly improved their error rate and completion time when we focus on the difference between the first and last trials. While this observation is attributable to a learning mechanism, another factor that comes into play is the warm-up process. Warm-up combats muscle and joint stiffness and could have aided the participants in a better performance in later trials (Bishop, 2003).

5.2 Qualitative Differences

Going from intermediate to expert – Conserving energy

Despite failing to estimate learning curves, we could still analyse the qualitative mannerism of the groups concerning their movement. The most obvious conclusion from the data at hand is that the intermediates have the highest velocity and acceleration. Based on these findings alone, one could question whether the intermediates might be more skilled at performing bronchoscopy on a simulator. Fast movements can serve as an indicator of skill, as speed is learned with repetition and experience. That is also why the novices report significantly slower movements than the experts or intermediates.

However, at some point, the speed reaches a limit in its effectiveness and speed that exceeds this limit brings about unnecessary fast movements. Setting the body in motion to reach fast acceleration and velocity requires force in the form of muscle activity, which consumes energy and overburdens the muscles. In the long run, the resulting muscle fatigue would likely affect the operator's handling precision, and the operator would need to take short breaks to let the muscles regenerate. This conclusion is backed up by the fact that the experts have the lowest completion time for the first task, and their time on task lessens more with each trial compared to the intermediates. Hence, fast movements did not automatically help the intermediates finish the task more quickly. Evidently, after learning to navigate through the airways successfully and safely with high speed, mastering bronchoscopy involves reducing the movement to the optimal level to preserve energy.

Efficiency or thoroughness

Although we have seen that the experts have the lowest completion time for task one, they have a higher error rate than the intermediates. They have touched the walls more often on average and stayed in contact with the wall for more seconds most of the time. This goes against our intuitive

reasoning that medical experts who have conducted more than 500 bronchoscopies get outperformed by someone with 5 – 100 operations. Nevertheless, there might be a logical explanation behind all of this. A promising candidate is the efficiency-thoroughness trade-off principle. This principle states that in specific situations, it is beneficial or inevitable to trade in efficiency against thoroughness (Kontogiannis & Malakis, 2019). Time is a limited resource in the medical context. The operation should not take too long. Otherwise, the doctor and medical staff are wasting time that they could spend helping other patients. Besides, the patients are often under the influence of anaesthesia; hence, there is also an ecological factor in play. While these two resources are often scarce, patient safety cannot be neglected. Accordingly, the expert must decide between efficiency by avoiding time waste or thoroughness by viewing patient safety as the highest priority. The problem with this explanation is that safety should have higher stakes than efficiency within the medical context (Baysari, 2020). Not only because patient well-being is the core aspect of medical procedures but also because one mistake on the operator's side can cause severe complications for the patient. Fixing these might be immensely time-consuming and costly in the end. Consequently, we expect experts to have adapted their movements to avoid making mistakes.

The relationship between the movement parameters and the outcome measures delivered an approach that would steer the experts toward thoroughness. An increase in unit acceleration, which has been centred around the mean, resulted in a lower completion time and more errors (ConWall). Thus, if we assume that experts should thrive for the least number of errors, the estimated average acceleration of the experts is a proper amount, as any increment results in more errors. Reversely, an increment in velocity is associated with a longer completion time but fewer errors. In conclusion, should experts favour efficiency in the form of completion time, they should try to boost their acceleration and regulate their velocity and vice versa in case they prioritise thoroughness. The question remains whether the experts can adapt their movement. Increasing velocity without simultaneously amplifying acceleration means that the bronchoscopist needs to keep a steady pace, which is difficult as acceleration and deceleration characterise flexible bronchoscopy.

Negative transfer

Most experts have conducted their bronchoscopies on actual patients and do not have substantial practice with simulated bronchoscopy. Over the years, experts have developed unconscious movement patterns and implicit interaction modes (Besnard & Cacitti, 2005). These help them to perform bronchoscopy in a short timeframe while also preserving cognitive resources. However, when the experts switch to simulated bronchoscopy, these implicit skills they have acquired outside of the simulator might inhibit them from performing properly due to negative transfer (Besnard & Cacitti, 2005).

Simulators aim at replicating the actual procedure, but there might be subtle differences between simulated bronchoscopy and operating on actual patients. The simulator might require slightly different movement of the handle or expect the operator to position their body at an unfamiliar angle. Since the experts are likely to assume that they can control simulated bronchoscopy the same as the real deal, they will automatically apply their implicit skills, disregarding the possibility that the simulator necessitates distinct movements. Of course, there is a primarily positive transfer between the actual and simulated bronchoscopy; otherwise, the novices would be the group with the best performance. However, these tiny dissimilarities could be enough for the experts to make a few more errors than the intermediates.

Although the intermediates have performed a considerable number of bronchoscopies on actual patients, they are not equally influenced by negative transfer for two reasons. First, many intermediates have had practice on the simulator in the recent past, so they know the discrepancies to real bronchoscopy. Second, intermediates are not as experienced as the experts yet. Whereas experts will rely on their intuitive skills even in novel and unexpected situations (during bronchoscopy), the intermediates will likely emphasise deliberate thoughts and use more cognitive resources to navigate the airways.

Error Recovery

Grazing the bronchial wall is considered an error and is the result of the participants positioning the bronchoscope incorrectly. In turn, this would mean they need to reorientate the bronchoscope, which should cost valuable time. We have gained the insight that experts make more mistakes than intermediates, but they finish the task more quickly. A probable explanation is that experts are punished less severely for making mistakes since they are better at recovering from errors. Due to their immense experience, it is plausible that they have already made these mistakes in the past and learned to deal with them efficiently.

5.3 The Expert Bronchoscopist

Velocity and acceleration in different directions

After we have put aside potential misunderstandings and clarified that the experts are the experts, after all, we can go into more detail about what characterises an expert bronchoscopist. Defining how an expert conducts bronchoscopy means looking at what body segments they utilise and in what direction they move. We start by taking a closer look at the hand and forearm. Recommendations for bronchoscopy have in common that they stress the importance of the hand in handling the bronchoscope. From a physical standpoint, it makes sense. The hand weighs less than the forearm or upper arm, requiring less force and energy to assert change on the bronchoscope's tip. Moreover, the hand is flexible, allowing for intense movements from the wrist. On the contrary, the hand on its own has a limited reach, and the wrist cannot be turned indefinitely. The role of the arm in bronchoscopy might, therefore, be of equal importance.

Indeed, the velocity of the hand and forearm is about equal for the experts when they proceed in the Y direction. In contrast, they accelerate more in the X direction. This would encompass that experts move their hand and forearm along the y-axis with a constant speed and when necessary, they execute short burst movements in the X direction. The Xsens software bases the y-axis on the righthanded coordinate system (West), meaning it proceeds alongside the torso from left to right. The xaxis points forward, away from the body. In more practical terms, we could say that the experts perform bronchoscopy by moving their forearm from left to right at a constant speed while accelerating their wrist away or towards their body on the x-axis. This way, they can utilize the reach they gain by moving their forearm and take advantage of the wrist's versatility in accommodating the angle of the bronchoscope's tip. We know that the experts used wrist movement since it is the only way of moving the hand without simultaneously moving the forearm. If they move their hand along the x-axis without turning the wrist, the forearm would indicate the same acceleration as the hand. As this is not the case, the experts employed additional wrist movements. *Figure 18* illustrates how this movement looked like in the Xsens software.

The experts and intermediates have a reversed movement. The intermediates have the greatest acceleration in the Y direction and velocity in the X direction. One observation that we can make from this pattern is that when speed is high in a particular direction, the acceleration is low in the same direction. When a body part is moved in a specific direction with a higher velocity, this velocity is mostly kept in equilibrium and does not undergo frequent change. In other words, the hand and forearm deaccelerate and accelerate more frequently when the velocity is kept at a minimum. This type of movement is called ballistic movement and defines burst movements that fire the maximum velocity and acceleration in a short time (Zehr & Sale, 1994).

The reason the experts and intermediates move their body parts in different directions remains a question to be answered. The education around bronchoscopy might have undergone a change in recent years, with new techniques being taught to intermediates that were not present when the experts began to learn bronchoscopy. Nevertheless, discovering these discrepancies highlights the importance of investigating the qualitative characteristics of the groups.



Figure 18 – The Xsens 3D character animation.

The arrows represent the direction: The red arrow = x-axis = forward and backwards, the blue arrow = y-axis = left and right, green arrow = z-axis = (up-down). The image was from retrieved from one of the recordings.

Moving the hand downwards

Advancing the hand and arm on the axes can go in two directions: The positive and negative directions. We have seen that experts and intermediates move the hand and the forearm with more velocity in the negative Z direction than in the positive Z direction. Gravity acts as a downward force making it easier to descend the hand. Gravity doubtlessly is a crucial factor to consider, but it is not the leading cause of this downward trend. The two tasks have in common that the bronchoscope itself, for the most part, needs to move downwards. For instance, the first task was achieved by following a blue ball through the airways and could be completed without retracting the bronchoscope. Only when the operator lost the orientation or turned the tip of the bronchoscope in the wrong direction was it helpful to retract the bronchoscope. Hence, movement dominantly going into the negative Z direction can be considered an indicator of expertise. That would also explain why the negative and positive direction of the novices is equally balanced out. They were forced to retract the tip to compensate for wrong movements.

Beginning to learn bronchoscopy

To get insight into the experts, we can look into their counterparts, the novices. All-embracing, the novices have the lowest acceleration and velocity. Since they have overall low values, outliers become readily apparent. The most vital outlier is the velocity of their upper arm. The velocity of their upper arm is on the same level as that of the experts and intermediates despite all other values

being drastically lower. Thus, we can assume that novices use their upper arm disproportionally frequently. Based on the concept of inertia, using the upper arm to operate the bronchoscope should be inefficient. The upper arm weighs considerably more than the hand or forearm, and accelerating the upper arm demands more force in the form of muscle activity. Therefore, a problem for novices appears to be regulating their upper arm. Either they have too much movement of the upper arm, or they start by optimising their upper arm instead of learning to control the hand and forearm correctly first. Both scenarios could explain why the novices did not report a continuous learning effect in the first five trials.

We gained another helpful insight when we modelled acceleration and velocity as covariates to predict the performance measures. With each increment in acceleration away from the group mean, the novices need considerably more time and make more errors. In section 2.8 (Understanding Movement – The Body in Motion), we have introduced the concept of jerk, which describes the change in acceleration over time. High jerk body motions lead to rapid change in acceleration making it hard or even impossible to control them. Unable to keep their jerk at a minimum, the novices end up performing short, uncontrollable bursts movements in one direction that cause them to make mistakes. In turn, the mistakes require ample time to recover due to the need to reallocate the bronchoscope. The experts have likely learned to raise their acceleration at a constant rate. It might not be a high acceleration that is difficult for the novices to handle, but the high rate at which acceleration itself is changing. As a result, most novices will try to minimize their mistakes and avoid deliberate acceleration altogether. Beginner bronchoscopist might be better off by steadily increasing their velocity before turning to the acceleration as this seems to lower their time on task and is less error-prone.

5.4 Limitations

This study is limited in a few aspects that inhibit us from drawing a final conclusion about the results. The most obvious limitation is the number of repetitions that made it difficult or even impossible to model learning curves. Next, the intermediates reported being more familiar with the simulator and the tasks of the simulator. Consequently, it cannot be excluded that the experts performed worse due to unfamiliarity with the simulator or the mentioned negative transfer. This limitation is not severe because simulated bronchoscopy replicates actual bronchoscopy to a great extent. A final limitation concerns the labelling of expert and intermediate bronchoscopists. Initially, the participant must have performed more than 500 bronchoscopies to be considered an expert. To be categorised as intermediate, 5 - 100 bronchoscopies were necessary. However, some participants conducted between 100 and 500 bronchoscopies. Due to a lack of data, these participants were not included but were labelled as intermediates. Hence, the contrast between intermediates and experts is blurred, and someone marked as intermediate could have performed on the level of an expert. Interestingly, learning curves based on the LACY model could have identified incorrectly categorised intermediates

by modelling the amplitude of each participant. An incorrectly labelled intermediate would have an amplitude in the range of the other experts.

5.5 Outline for Future Research

Based on the limitations, it is already evident what future research can do to improve the study design. If a researcher is interested in predicting the performance and movement after X number of repetitions, then they can reconstruct this study with more repetitions. Similar studies should aim at balancing the experience that the groups have with simulated bronchoscopies. For instance, experts could get a more thorough introduction to simulated bronchoscopy and a few training sessions to bring them on the same level as the intermediates. This would reveal whether the experts make more mistakes because of negative transfer or because they try to be more efficient and accept that it comes with the cost of potential errors.

Apart from the limitations, this study delivered an exciting perspective on the qualitative differences between expert, intermediate and novice bronchoscopists. We learned that experts move their hand and forearm more slowly than intermediates, hold a constant speed when moving along their torso on the y-axis, and accelerate more when they move the bronchoscope away from and towards their torso. Since this study is the first of its kind, it is essential to strengthen these results by means of replication. If the results are replicable, we can draw a more robust conclusion about the behaviour of the experts, intermediates, and novices. Ultimately, these results can then be used to develop criteria bronchoscopists need to attain before operating on real patients. This way, whether someone can operate on patients would no longer be in the hands of costly and subjective expert assessments.

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Appendix A: Participant Information Sheet, Informed Consent, Ethical Approval

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.

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.

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.

Consent Form for Oscillatory dynamics of motor sequence learning expertise in the elderly

YOU WILL BE GIVEN A COPY OF THIS INFORMED CONSENT FORM

Please tick the appropriate boxes Taking part in the study Yes No

I have read and understood the study inform been read to me. I have been able to ask que answered to my satisfaction.			0	0
I consent voluntarily to be a participant in th questions and I can withdraw from the study			\bigcirc	0
I understand that taking part in the study inv performed on the computer with video recor	•	<u> </u>	\bigcirc	0
Use of the information in the study				
I understand that information I provide will be used for publication, conference presentation and scientific reports.			0	\bigcirc
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 <i>data</i> that I provide to be archived in BMS Datavault and made anonymous so it can be used for future research and learning.			\bigcirc	\bigcirc
I agree that my information may be shared w may be similar to this study or may be comp researchers will not include any information contact me for additional permission to use t	letely different. The ir that can directly ident	nformation shared with other	0	0
I give the researchers permission to keep my research projects.	v contact information a	and to contact me for future	\bigcirc	\bigcirc
Signatures				
Name of participant [printed]	Signature	Date		
I have accurately read out the information sh my ability, ensured that the participant under		-		
Researcher name [printed]	Signature	Date		
Contact Information for Questions about If you have questions about your rights as a information, ask questions, or discuss any co other than the researcher(s), please contact th	research participant, o oncerns about this stud	r wish to obtain y with someone		

Appendix B: Information Form - Motion Analysis

Personal details Name		
Age		
Sex	Female 🗌 Male 🔄 Other 📃	
Preferred hand	Left Right 🗌 No preference 🗌	
But bronchoscopy wit Date	h left 🔲	
City		
How many years have	e you been working as a pulmonology resident?	
Simulation experience Have you ever particip Yes No	e pated in a bronchoscopy simulation training?	
Bronchoscopy experie How many bronchosc bronchosco	opies did you perform in the past three months?	
How many bronchosc	opies did you perform in the <u>past yea</u> r?	bronchoscopies
How many bronchosc	opies did you perform in <u>your career so fa</u> r? opies	
Game experience		
Do you play video gan Yes No	nes requiring good eye-hand coordination?	
If yes, how often have	e you done so in the past year?	
hours per week		
or		
hours per month		
or		
hours per year		

Appendix C: R Syntax - Data Manipulation

```
library(rlang)
library(vctrs)
library(tidyverse)
library(brms)
library(bayr)
library(readxl)
library(data.table)
library(rstan)
library(dplyr)
library(boot)
library(ctsem)
library(stringr)
library(writexl)
library(StanHeaders)
library(unpivotr)
library(tidytext)
library(zoo)
library(pacman)
library(clipr)
library(patchwork)
library(gghighlight)
pacman::p load gh("bbc/bbplot")
```

##Data Manipulation of Original Data Sets + ## Creating the Final Data

```
outcome_vars <- c("RH_X", "RH_Y", "RH_Z", "RUA_X", "RUA_Y", "RUA_Z", "
RFA_X", "RFA_Y", "RFA_Z", "RH_X", "RH_Y", "RH_Z", "LUA_X", "LUA
_Y",
         "LUA_Z",
                      "LFA_X",
                                  "LFA_Y",
                                               "LFA_Z",
                                                            "LH_X", "LH_Y", "L
H_Z")
RawData <- read excel("AllDataSets.xlsx", sheet = 1) %>%
  pivot_longer(outcome_vars, names_to = "Sensor")
RawData2 <- read_excel("AllDataSets.xlsx", sheet = 2) %>%
  pivot_longer(outcome_vars, names_to = "Sensor")
#Turning the values to numeric
RawData<- mutate(RawData, value = as.numeric(value))</pre>
## for some data sets the values were defined as string or logical so this
code turns them back into numeric
#Check if there are values above 1000000 or below -1000000
filter(RawData, value > 1000 | value < -1000)</pre>
## In case there are values above 1000000 or below -1000000, you need to r
un the section below
Decimal <- function(x) {</pre>
ifelse(x >= 1000000, x/1000000, x*1)
```

```
}
DecimalN <- function(x) {</pre>
  ifelse(x <= -1000000, x/1000000, x*1)
}
RawData <- mutate(RawData, value = Decimal(value))</pre>
RawData <- mutate(RawData, value = DecimalN(value))</pre>
## run this section if there are values above 1000000 or below -1000000
## don't forget to run the segments containing the functions first (see ab
ove)
RawData <- RawData %>%
  group_by(Participant, Trial, Task, Measure) %>%
  mutate(RowLength = row_number())
RawData <- RawData %>%
  group_by(Trial, Participant, Task, Measure) %>%
  mutate(AbsoluteLength = n())
RawData <- RawData %>%
  group by(Participant, Trial, Task, Measure) %>%
  mutate(Time = if_else(RowLength <= n()/5, 1,</pre>
                         if_else(RowLength > n()%/%5 & RowLength <= n()%/%2
.5, 2,
                         if_else(RowLength > n()%/%2.5 & RowLength <= n()%/
%1.667, 3,
                         if else(RowLength > n()%/%1.667 & RowLength <= n()
%/%1.25, 4,
                         if_else(RowLength > n()%/%1.25 & RowLength <= n(),
5, 10))))))
#Extracting the mean value of each participant for the positive and negati
ve movement
options(digits = 8)
options(max.print=100000)
Neg <- filter(RawData, value < 0)
Pos <- filter(RawData, value >= 0)
Final1Neg <- aggregate(Neg$value, list(Neg$Participant, Neg$Trial, Neg$Tas</pre>
k, Neg$Sensor, Neg$Measure, Neg$Time), mean)
Final1Pos <- aggregate(Pos$value, list(Pos$Participant, Pos$Trial, Pos$Tas</pre>
k, Pos$Sensor, Pos$Measure, Pos$Time), mean)
Final1Neg <- rename(Final1Neg, Participant = Group.1, Trial = Group.2, Tas</pre>
k = Group.3, Sensor = Group.4, Measure = Group.5, Time = Group.6, value =
X)
Final1Pos <- rename(Final1Pos, Participant = Group.1, Trial = Group.2, Tas</pre>
k = Group.3, Sensor = Group.4, Measure = Group.5, Time = Group.6, value =
X)
Final1 <- rbind(Final1Neg, Final1Pos)</pre>
```

```
RawData2 <- RawData2 %>%
  group_by(Participant, Trial, Task, Measure) %>%
  mutate(RowLength = row number())
RawData2 <- RawData2 %>%
  group_by(Trial, Participant, Task, Measure) %>%
  mutate(AbsoluteLength = n())
RawData2 <- RawData2 %>%
  group_by(Participant, Trial, Task, Measure) %>%
  mutate(Time = if else(RowLength <= n()/5, 1,</pre>
                         if_else(RowLength > n()%/\% & RowLength <= n()%/\%
.5, 2,
                         if_else(RowLength > n()%/%2.5 & RowLength <= n()%/
%1.667, 3,
                         if else(RowLength > n()%/%1.667 & RowLength <= n()
%/%1.25, 4,
                         if else(RowLength > n()%/%1.25 & RowLength <= n(),
5, 10))))))
#Extracting the mean value of each participant for the positive and negati
ve movement
options(digits = 8)
options(max.print=100000)
Neg2 <- filter(RawData2, value < 0)
Pos2 <- filter(RawData2, value >= 0)
Final2Neg <- aggregate(Neg2$value, list(Neg2$Participant, Neg2$Trial, Neg2</pre>
$Task, Neg2$Sensor, Neg2$Measure, Neg2$Time), mean)
Final2Pos <- aggregate(Pos2$value, list(Pos2$Participant, Pos2$Trial, Pos2</pre>
$Task, Pos2$Sensor, Pos2$Measure, Pos2$Time), mean)
Final2Neg <- rename(Final2Neg, Participant = Group.1, Trial = Group.2, Tas</pre>
k = Group.3, Sensor = Group.4, Measure = Group.5, Time = Group.6, value =
X)
Final2Pos <- rename(Final2Pos, Participant = Group.1, Trial = Group.2, Tas</pre>
k = Group.3, Sensor = Group.4, Measure = Group.5, Time = Group.6, value =
x)
Final2 <- rbind(Final2Neg, Final2Pos)</pre>
Final2 <- Final2 %>% mutate(Trial = if else(Trial == 6, 1,
                                             if else(Trial == 7, 2,
                                             if_else(Trial == 8, 3, Trial*1
))))
FinalDf <- rbind(Final1, Final2)</pre>
FinalDf <- FinalDf %>% mutate(Sign = if else(value < 0, "N", "P"))</pre>
TimesNegativ <- function (x) {ifelse(x < 0, x * -1, x * 1) }
FinalDf <- FinalDf %>% mutate(value = TimesNegativ(value))
```

```
DesTask1 <- read_excel("AllDataSets.xlsx", sheet = 3)</pre>
DesTask3 <- read_excel("AllDataSets.xlsx", sheet = 4)</pre>
FinalTask1 <- FinalDf %>%
  filter(Task == 1) %>%
  arrange(Participant) %>%
  select(Trial, Participant, Sensor, value, Measure, Trial, Time, Sign, Ta
sk) %>%
  pivot wider(names from = c(Sensor, Measure, Sign, Time), values from = v
alue)
FinalTask3 <- FinalDf %>%
  filter(Task == 3) %>%
  arrange(Participant) %>%
  select(Trial, Participant, Sensor, value, Measure, Trial, Time, Sign, Ta
sk) %>%
  pivot_wider(names_from = c(Sensor, Measure, Sign, Time), values_from = v
alue)
FinalTask1 <- FinalTask1 %>% mutate(ToT = DesTask1$ToT) %>%
  mutate(ConWall = DesTask1$ConWall) %>%
  mutate(Proficiency = DesTask1$Proficiency) %>%
  mutate(DomHand = DesTask1$DomHand) %>%
  mutate(TimeWall = DesTask1$TimeWall)
FinalTask3 <- FinalTask3 %>% mutate(ToT = DesTask3$ToT) %>%
  mutate(ConWall = DesTask3$ConWall) %>%
  mutate(Proficiency = DesTask3$Proficiency) %>%
  mutate(DomHand = DesTask3$DomHand) %>%
  mutate(TimeWall = DesTask3$TimeWall)
FinalDf <- rbind(FinalTask1, FinalTask3)</pre>
outcome_vars2 <- FinalDf %>% select(-Trial, -Participant, -ConWall, -TimeW
all, -ToT, -Proficiency, -DomHand, -Task) %>%
  colnames()
FinalDf <- FinalDf %>%
    pivot_longer(outcome_vars2, names_to = "Sensor") %>%
      separate(Sensor, into = c("Position", "Axis", "Measure", "Sign", "Ti
me"))
filter(FinalDf, DomHand == "L" & Position =="RUA")
HandLeft <- FinalDf %>% filter(DomHand == "L") %>% filter(Position != "RH"
& Position != "RFA" & Position != "RUA")
HandRight <- FinalDf %>% filter(DomHand == "R") %>% filter(Position != "LH
" & Position != "LFA" & Position != "LUA")
FinalDf <- rbind(HandLeft, HandRight)</pre>
FinalDf <- FinalDf %>% replace(FinalDf == "LH", "Hand") %>%
replace(FinalDf == "LFA", "FoArm") %>%
```

```
replace(FinalDf == "LUA", "UpArm") %>%
replace(FinalDf == "RH", "Hand") %>%
  replace(FinalDf == "RFA", "FoArm") %>%
  replace(FinalDf =="RUA", "UpArm")
## Run this code to obtain the values for the overall acceleration and vel
ocity
MeanSquared <- FinalDf %>%
  select(Participant, Trial, Position, Proficiency, Task, Measure, Axis, S
ign, Time,value) %>%
  pivot_wider(names_from = Sign, values from = value)
MeanSquared <- mutate(MeanSquared, Movement = (P+N)/2) %>%
  pivot_longer(c(P,N), names_to = "Sign")
FinalDf <- merge(FinalDf, MeanSquared, by = c("Participant", "Trial", "Pos</pre>
ition", "Axis", "Proficiency", "Task", "Measure", "Sign", "Time", "value"
))
FinalDf <- FinalDf %>% group_by(Participant, Trial, Task, Measure, Positio
n, Axis, Sign) %>%
  mutate(SumValue = mean(value)) %>%
  mutate(SumMovement = mean(Movement)) %>%
  mutate(Time = as.numeric(Time))
write xlsx(FinalDf, "C:\\Users\\marce\\OneDrive\\Dokumente\\Psychology\\Ma
ster Year\\Master Thesis\\R Analysis\\FinalDf.xlsx")
## Movement -> averaged over negative and positive values
## SumValue -> averaged over the five sections
## SumMovement -> averaged over positive and negative values as well as th
e five sections
```

Final Data Set

```
D_1 <- read_excel("FinalDf.xlsx") %>%
group_by(Participant, Trial, Position, Measure, Task, Time, Sign) %>%
mutate(XYZ = mean(value)) %>%
fulter(SumXYZ = mean(XYZ)) %>%
filter(ToT > 9)
D_2 <- D_1 %>% filter(Time == 1) %>% ## SumValue without aggregation
select(-value, -Time, -SumMovement, -Movement, -XYZ, -SumXYZ) %>%
pivot_wider(names_from = Measure, values_from = SumValue) %>%
mutate(Velocity = if_else(is.na(Velocity) & Participant == 12, 0.0248816
6, Velocity)) %>%
mutate(Velocity = if_else(is.na(Velocity) & Participant == 17, 0.0050267
1, Velocity)) %>%
mutate(ConWall = as.numeric(ConWall))
```

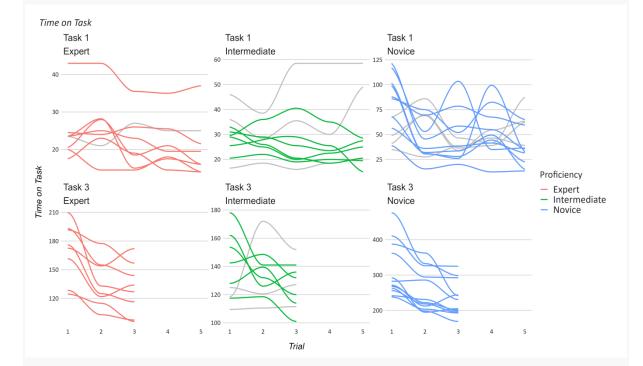
Appendix D: R Syntax – Data Analysis

```
library(rlang)
library(vctrs)
library(tidyverse)
library(brms)
library(bayr)
library(readxl)
library(data.table)
library(rstan)
library(dplyr)
library(boot)
library(ctsem)
library(stringr)
library(writexl)
library(StanHeaders)
library(unpivotr)
library(tidytext)
library(zoo)
library(pacman)
library(clipr)
library(patchwork)
library(gghighlight)
pacman::p_load_gh("bbc/bbplot")
```

Exploratory Analysis

```
```{r}
namesTask = c("Task 1","Task 3")
names(namesTask) = c("1", "3")
D 3 <- D 2 %>%
 select(-TimeWall, -Acceleration, -ConWall, -Velocity) %>%
 mutate(Trial = paste0("T", Trial)) %>%
 pivot_wider(names_from = Trial, values_from = ToT) %>%
 group_by(Task, Participant, Proficiency) %>%
 mutate(Trial HL = if else(Task == 1 & T1 > T5, 1,
 if_else(Task == 3 & T1 > T3, 1, 0))) %>%
 pivot_longer(c(T1, T2, T3, T4, T5), names_to = "Trial") %>%
 mutate(Trial = gsub("T", "", Trial),
 Trial = as.numeric(Trial))
ToT Spag <- suppressWarnings(print(D 3 %>% filter(Position == "Hand" & Axi
s == "X" & Sign == "N") %>%
 ggplot(aes(x = Trial)) +
 geom_smooth(aes(y = value, group = Participant, color = Proficiency), se
= F) +
 facet_wrap(Task~Proficiency, scale = "free_y",
 labeller = labeller(Task = namesTask)) +
 gghighlight(calculate_per_facet = TRUE, Trial_HL == 1,
 unhighlighted_params= list(colour = alpha("grey", 1))) +
 labs(x = "Trial", y = "Time on Task",
 title = "Time on Task") +
```

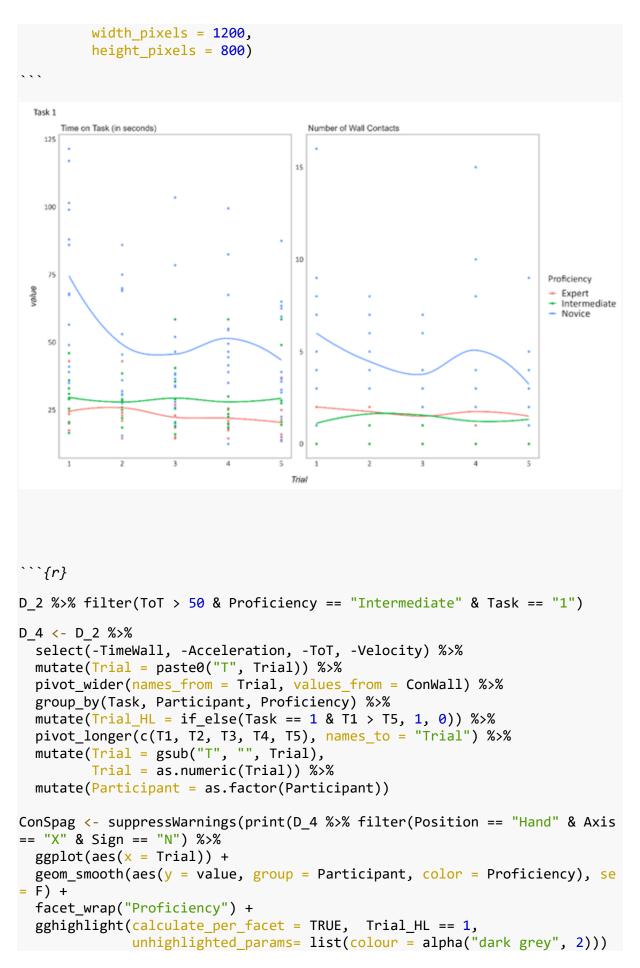
bbc\_style\_R()))



# $```{r}$

namesMeasure = c("Time on Task (in seconds)", "Number of Wall Contacts")
names(namesMeasure) = c("ToT", "ConWall")

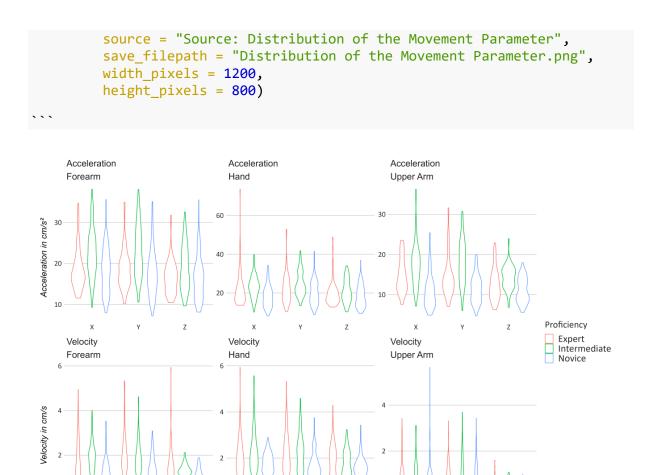
```
PopLvl <- suppressWarnings(print(D_2 %>% filter(Task == "1", Position == "
Hand" & Axis == "X" & Sign == "N") %>%
 pivot_longer(c("ConWall", "ToT"), names_to = "Measure") %>%
 mutate(Measure = factor(Measure, levels = c("ToT", "ConWall"))) %>%
 ggplot(aes(y = value, x = Trial, color = Proficiency)) +
 geom point() +
 geom_smooth(aes(Group = Proficiency), se = F) +
 facet_wrap("Measure", scale = "free_y",
 labeller = as labeller(c(ToT = "Time on Task (in seconds)", C
onWall = "Number of Wall Contacts"))) +
 labs(subtitle = "Task 1") +
 theme(panel.border = element_rect(colour = "grey", fill=NA, size=2)) +
 bbc_style_R()))
finalise_plot(plot_name = PopLvl,
 source = "Source: Population Level",
 save_filepath = "Population Level.png",
```



```
+
 labs(x = "Trial", y = "Number of Wall Contacts",
 title = "Number of Wall Contacts", subtitle = "Task 1") +
 scale_y_continuous(breaks = scales::pretty_breaks(n = 10)) +
 bbc_style_R()))
finalise_plot(plot_name = ConSpag,
 source = "Source: ConWall Spaghetti",
 save filepath = "ConWall Spaghetti.png",
 width_pixels = 1200,
 height pixels = 800)
. . .
 Number of Wall Contacts
 Task 1
 Expert
 Intermediate
 Novice
 16
 14
 12
 Number of Wall Contacts
 10
 Proficiency
 Expert
 - Intermediate

 Novice

 6
 4
 2
 0
 1
 2
 3
 4
 5
 1
 2
 3
 4
 5
 1
 2
 3
 4
 5
 Trial
```{r}
NamesPosition <- c("Hand", "Forearm", "Upper Arm")</pre>
names(NamesPosition) <- c("Hand", "FoArm", "UpArm")</pre>
Mov_Dis <- D_1 %>% filter(Time == 1 & Task == 1) %>%
  mutate(SumValue = SumValue * 100) %>%
  ggplot(aes(y = SumValue, x = Axis, color = Proficiency)) +
  geom_violin() +
  facet_wrap(Measure ~ Position, scale = "free_y",
               labeller = labeller(Position = NamesPosition)) +
  labs(x = "Direction", y = "Velocity in cm/s
Acceleration in cm/s<sup>2</sup>") +
  bbc_style_R()
finalise_plot(plot_name = Mov_Dis,
```



Multivariate Model – Acceleration and Velocity

Z

Y

Direction

Z

Tibbles

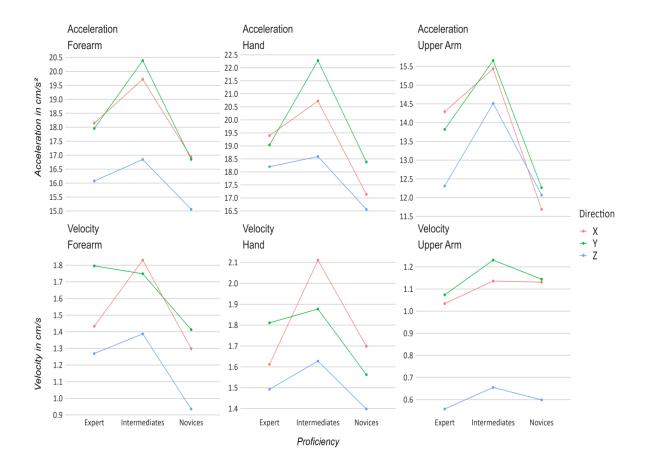
0

```
\sum{r}
T_M_1 <- as.tibble(coef(M_1)) %>%
  separate(parameter, into = c("b", "Rest"), sep = "b_") %>%
  separate(Rest, into = c("DV", "Rest", "BodyDir"), sep = "_") %>%
  mutate(Rest = if_else(str_detect(Rest, "Proficiency"), Rest, paste0("Pro
ficiencyExpert:", Rest))) %>%
  separate(Rest, into = c("Proficiency", "IV"), sep = ":") %>%
  mutate(IV = if_else(is.na(IV), "Intercept", IV)) %>%
  mutate(Proficiency = gsub("Proficiency", "", Proficiency)) %>%
  select(DV, Proficiency, IV, BodyDir, center, lower, upper) %>%
 mutate(IV = gsub("PosAxis", "", IV)) %>%
  mutate(BodyDir = if_else(!is.na(BodyDir), paste(IV, BodyDir), BodyDir))
%>%
  mutate(BodyDir = gsub(" ", "_", BodyDir)) %>%
  mutate(IV = if_else(!is.na(BodyDir), "PosAxis", IV)) %>%
  mutate(BodyDir = if else(is.na(BodyDir) & IV == "Intercept", "Hand X", B
odyDir))
• • •
CLU Trial <- c("center_Intercept", "center_Trial", "lower_Intercept", "low
er_Trial", "upper_Intercept", "upper_Trial")
Estimates <- c("center_Expert", "center_Intermediate", "center_Novice", "l</pre>
ower_Expert", "lower_Intermediate", "lower_Novice", "upper_Expert", "upper
_Intermediate", "upper_Novice")
```{r}
T M 2 <- T M 1 %>%
 pivot wider(names from = Proficiency, values from = c(center, lower, upp
er)) %>%
 mutate(across(center_Intermediate:center_Novice,~.+center_Expert)) %>%
 mutate(across(lower Intermediate:lower Novice, ~. + center Expert)) %>%
 mutate(across(upper Intermediate:upper Novice, ~.+center Expert)) %>%
 pivot_longer(Estimates, names_to = "Estimate") %>%
 separate(Estimate, into = c("Estimate", "Proficiency")) %>%
 pivot wider(names from = Estimate, values from = value)
T_M_3 <- T_M_2 %>%
 select(-BodyDir) %>%
 filter(IV == "Intercept" | IV == "Trial") %>%
 pivot_wider(names_from = IV, values_from = c(center, lower, upper)) %>%
 mutate(center Intercept = center Intercept + center Trial) %>%
 mutate(lower_Intercept = lower_Intercept + lower_Trial) %>%
 mutate(upper_Intercept = upper_Intercept + upper_Trial) %>%
 pivot_longer(CLU_Trial, names_to = "IV") %>%
 separate(IV, into = c("CLU", "IV")) %>%
 pivot wider(names from = CLU, values from = value)
• • •
```

### Visual Analysis

 $```{r}$ 

```
NamesPosition <- c("Hand", "Forearm", "Upper Arm")</pre>
names(NamesPosition) <- c("Hand", "FoArm", "UpArm")</pre>
Mov <- T M 2 %>%
 filter(IV == "PosAxis" | IV == "Intercept") %>%
 select(-lower, -upper, -IV) %>%
 pivot_wider(names_from = BodyDir, values_from = center) %>%
 mutate(across(Hand_Y:UpArm_Z,~.+Hand_X)) %>%
pivot_longer(c("Hand_X", "Hand_Y", "Hand_Z", "FoArm_X", "FoArm_Y", "FoAr
m_Z", "UpArm_X", "UpArm_Y", "UpArm_Z"), names_to = "BodyDir") %>%
 separate(BodyDir, into = c("Position", "Direction")) %>%
 ggplot(aes(x = Proficiency, y = value, color = Direction)) +
 geom_point() +
 geom_line(aes(group = Direction)) +
 scale_x_discrete(labels = c("Expert", "Intermediates", "Novices")) +
 facet_wrap(DV ~ Position, labeller = labeller(Position = NamesPosition),
scale = "free_y") +
 labs(x = "Proficiency", y = "Velocity in cm/s
Acceleration in cm/s^2") +
 scale_y_continuous(breaks = scales::pretty_breaks(n = 10)) +
 bbc_style_R()
finalise_plot(plot_name = Mov,
 source = "Figure 7",
 save filepath = "Difference in Movement.png",
 width pixels = 900,
 height pixels = 600)
```



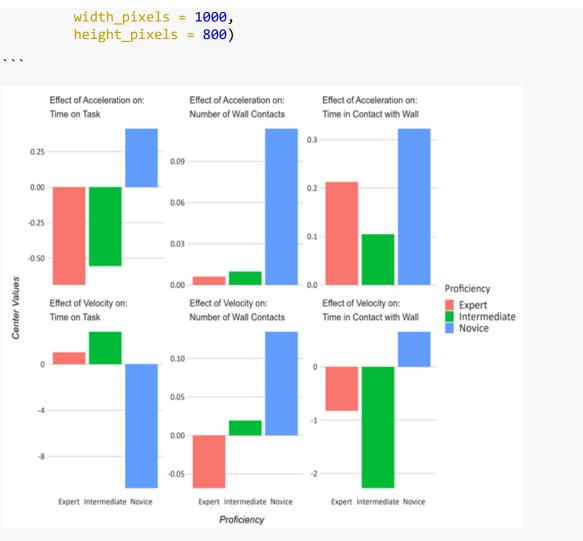
### Multivariate Model – Tot, ConWall and TimeWall

```
\sum{r}
bf ToT <- bf(ToT | subset(Sub1) ~ Proficiency * (Trial + Task + SumAcc + S</pre>
umVel)) + exgaussian()
bf_TimeWall <- bf(TimeWall | subset(Sub1) ~ Proficiency * (Trial + Task +</pre>
ToT + SumAcc + SumVel)) + hurdle gamma()
bf_ConWall <- bf(ConWall | subset(Sub2) ~ Proficiency * (Trial + ToT + Sum</pre>
Acc + SumVel)) + negbinomial()
M_2 <- D_2 %>%
 group by(Participant, Trial, Task, Proficiency) %>%
 mutate(SumAcc = mean(Acceleration) * 100,
 SumVel = mean(Velocity) * 100) %>%
 ungroup() %>%
 mutate(SumAcc = SumAcc - mean(SumAcc)) %>%
 mutate(SumVel = SumVel - mean(SumVel)) %>%
 group_by(Participant, Trial, Task) %>%
 mutate(Sub1 = if_else(duplicated(ToT), 0, 1)) %>%
 mutate(Sub2 = if_else(duplicated(ConWall) | Task == 3, 0, 1)) %>%
 ungroup() %>%
```

```
unite(PosAxis, c(Position, Axis), remove = FALSE) %>%
 mutate(PosAxis = factor(PosAxis, levels = c("Hand_X", "Hand_Y", "Hand_Z"
, "FoArm_X", "FoArm_Y", "FoArm_Z", "UpArm_X", "UpArm_Y", "UpArm_Z"))) %>%
 mutate(Task = as.factor(Task),
 ConWall = as.integer(ConWall),
 TimeWall = as.numeric(TimeWall),
 TimeWall = TimeWall + 1) %>%
 brm(bf_ToT + bf_ConWall + bf_TimeWall + set_rescor(FALSE), data = ., cha
ins = 6, cores = 6, iter = 3000, warmup = 1500, init = 0)
. . .
```{r}
Estimates <- c("center_Expert", "center_Intermediate", "center_Novice", "1</pre>
ower_Expert", "lower_Intermediate", "lower_Novice", "upper_Expert", "upper
_Intermediate", "upper_Novice")
CLU_Trial <- c("center_Intercept", "center_Trial", "lower_Intercept", "low
er_Trial", "upper_Intercept", "upper_Trial", "center_Task3", "lower_Task3"
, "upper_Task3")
T M 4 <- as.tibble(coef(M 2)) \%
  separate(parameter, into = c("b", "Rest"), sep = "b_") %>%
  separate(Rest, into = c("DV", "Rest"), sep = "_") %>%
  mutate(Rest = if_else(str_detect(Rest, "Proficiency"), Rest, paste0("Pro
ficiencyExpert:", Rest))) %>%
  separate(Rest, into = c("Proficiency", "IV"), sep = ":") %>%
  mutate(IV = if_else(is.na(IV), "Intercept", IV)) %>%
  mutate(Proficiency = gsub("Proficiency", "", Proficiency)) %>%
  select(DV, Proficiency, IV, center, lower, upper) %>%
 mutate(DV = factor(DV, levels = c("ToT", "ConWall", "TimeWall")))
• • •
```{r}
T M 4 <- T M 4 %>%
 pivot_wider(names_from = Proficiency, values_from = c(center, lower, upp
er)) %>%
 mutate(across(center_Intermediate:center_Novice,~.+center_Expert)) %>%
 mutate(across(lower Intermediate:lower Novice,~.+center Expert)) %>%
 mutate(across(upper_Intermediate:upper_Novice, ~.+center_Expert)) %>%
 pivot_longer(Estimates, names_to = "Estimate") %>%
 separate(Estimate, into = c("Estimate", "Proficiency")) %>%
 pivot_wider(names_from = Estimate, values_from = value) %>%
 pivot_longer(c(center, lower, upper), names_to = "Estimate") %>%
 mutate(value = if_else(DV != "ToT", exp(value), value)) %>%
 pivot wider(names from = Estimate, values from = value)
T_M_4 <- T_M_4[order(T_M_4$Proficiency),]</pre>
```

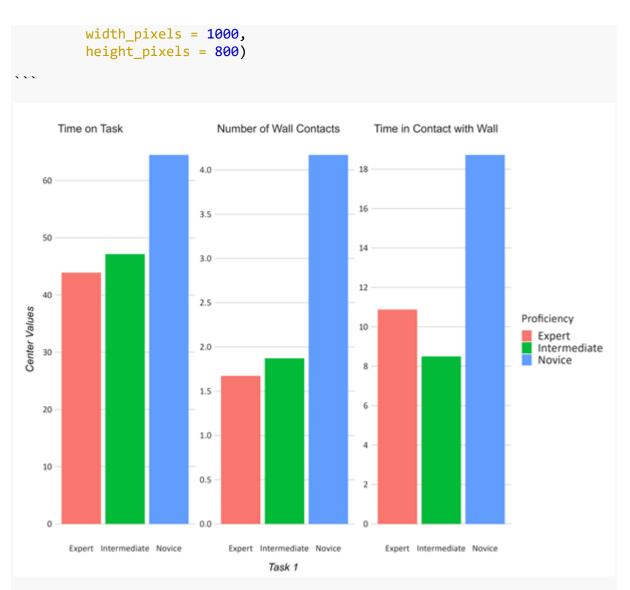
 $\sum{r}$ 

```
CLU_Trial <- c("center_Intercept", "center_Trial", "lower_Intercept", "low
er_Trial", "upper_Intercept", "upper_Trial")
T M 5 <- T M 4 %>%
 filter(IV == "Trial" | IV == "Intercept") %>%
 pivot_wider(names_from = IV, values_from = c(center, lower, upper)) %>%
 mutate(center_Intercept = center_Intercept + center_Trial) %>%
 mutate(lower Intercept = lower Intercept + lower Trial) %>%
 mutate(upper Intercept = upper Intercept + upper Trial) %>%
 pivot longer(CLU Trial, names to = "IV") %>%
 separate(IV, into = c("CLU", "IV")) %>%
 pivot_wider(names_from = CLU, values_from = value) %>%
 filter(IV == "Intercept")
T_M_5 <- T_M_5[order(T_M_5$Proficiency),]</pre>
Visual Analysis
```{r}
NamesIV <- c("Effect of Acceleration on:", "Effect of Velocity on:", "Time
on Task")
names(NamesIV) <- c("SumAcc", "SumVel", "ToT")</pre>
NamesDV <- c("Time on Task", "Number of Wall Contacts", "Time in Contact w</pre>
ith Wall")
names(NamesDV) <- c("ToT", "ConWall", "TimeWall")</pre>
MovSlope <- T M 4 %>%
  select(-lower, -upper) %>%
  filter(IV == "SumVel" | IV == "SumAcc" | IV == "Intercept") %>%
  pivot wider(names from = IV, values from = center) %>%
  mutate(SumAcc = if else(DV != "ToT", Intercept * (SumAcc - 1), SumAcc))
%>%
  mutate(SumVel = if_else(DV != "ToT", Intercept * (SumVel - 1), SumVel))
%>%
  pivot_longer(c("Intercept", "SumAcc", "SumVel"), names_to = "IV") %>%
  filter(IV != "Intercept") %>%
  ggplot(aes(x = Proficiency, y = value, fill = Proficiency)) +
  geom_bar(stat="identity", position=position_dodge()) +
  facet_wrap(IV ~ DV, scale = "free_y",
             labeller = labeller(IV = NamesIV, DV = NamesDV)) +
  labs(x = "Proficiency", y = "Center Values") +
  theme(strip.text = element text(size = 3)) +
  bbc style R()
finalise_plot(plot_name = MovSlope,
         source = "Source: Movement Slopee",
         save_filepath = "Movement Slope.png",
```



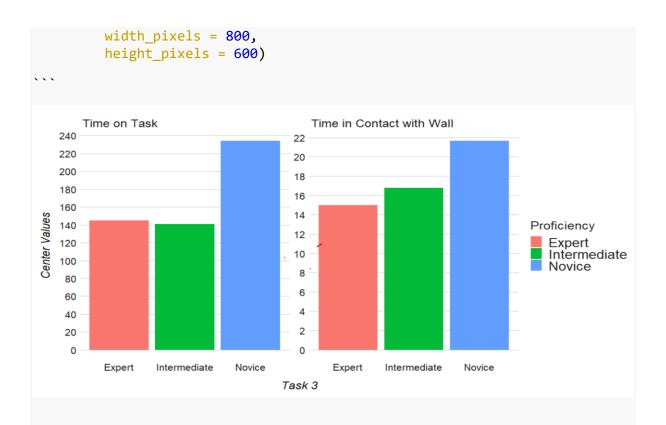
```{r}

```
NamesDV <- c("Time on Task", "Number of Wall Contacts", "Time in Contact w
ith Wall")
names(NamesDV) <- c("ToT", "ConWall", "TimeWall")</pre>
```



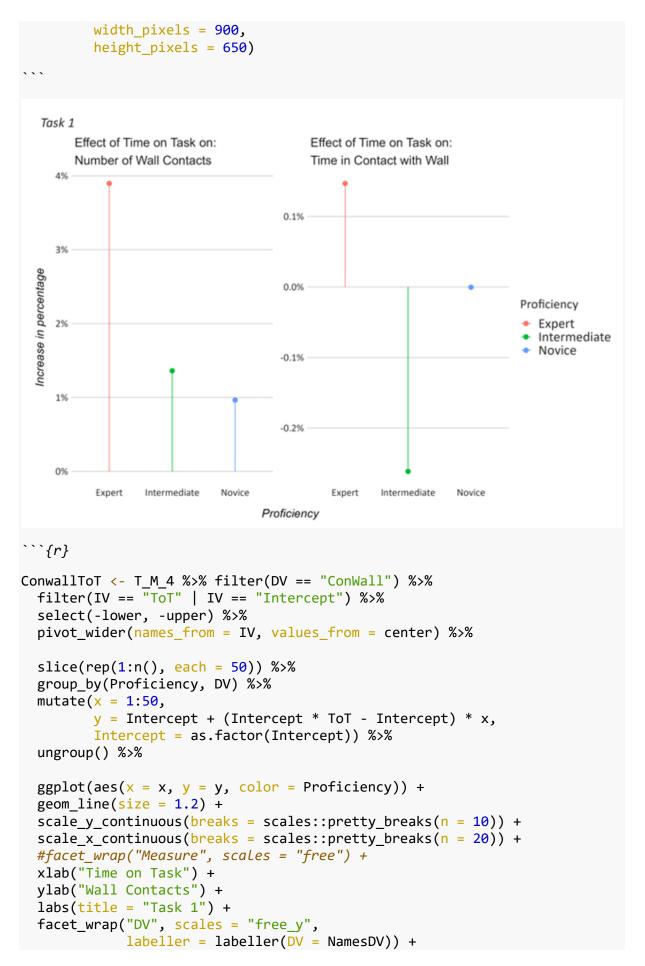
```
```{r}
```

```
PerfMeas3 <- T M 5 %>%
  select(-lower, -upper) %>%
 filter(IV == "Intercept" & DV != "ConWall" | IV == "Task3" & DV != "ConW
all") %>%
  pivot_wider(names_from = IV, values_from = center) %>%
  mutate(Intercept = Intercept + Task3) %>%
  ggplot(aes(x = Proficiency, y = Intercept, fill = Proficiency)) +
  geom_bar(stat="identity", position=position_dodge()) +
  scale_y_continuous(breaks = scales::pretty_breaks(n = 10)) +
  xlab("Task 3") +
  ylab("Center Values") +
  facet_wrap("DV", scale = "free_y",
             labeller = labeller(DV = NamesDV)) +
  bbc_style_R()
finalise plot(plot name = PerfMeas3,
         source = "Source: Performance Measures",
         save_filepath = "Performance Measures 3.png",
```



$```{r}$

```
NamesIV <- c("Effect of Time on Task on:", "Number of Wall Contacts", "Tim
e in Contact with Wall (in percentage)", "Time in Contact with Wall (in s
econds)")
names(NamesIV) <- c("ToT", "ConWall", "TimeWall", "SecondsWall")</pre>
SlopeToT <- T M 4 %>% filter(DV == "ConWall" | DV == "TimeWall") %>%
  filter(IV == "ToT") %>%
  select(-lower, -upper) %>%
  filter(IV != "Task3") %>%
  mutate(center = center - 1) %>%
  ggplot(aes(x = Proficiency, y = center, color = Proficiency)) +
  geom point(size = 3) +
  geom segment(aes(x=Proficiency,
                   xend=Proficiency,
                   y=0,
                   yend=center)) +
  facet wrap(IV ~ DV, scales = "free y",
             labeller = labeller(DV = NamesDV, IV = NamesIV)) +
  scale_y_continuous(breaks = scales::pretty_breaks(n = 10)) +
  scale_y_continuous(labels = scales::percent) +
  xlab("Proficiency") +
  ylab("Increase in percentage") +
  labs(title = "Task 1") +
  bbc style R()
finalise_plot(plot_name = SlopeToT,
         source = "",
         save_filepath = "Slope on ConWall.png",
```



```
bbc_style_R()
finalise_plot(plot_name = ConwallToT,
             source = "",
            save filepath = "ConWall over Time.png",
            width_pixels = 900,
            height_pixels = 700)
• • •
   Task 1
         Number of Wall Contacts
     4.5
     4.0
     3.5
  Vall Contacts
                                                                                       Proficiency
     3.0

    Expert

    Intermediate

     2.5

    Novice

      2.0
     1.5
      1.0
          0 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50 52
                                         Time on Task
```{r}
NamesIV <- c("Time on Task", "Number of Wall Contacts", "Time in Contact w
ith Wall (in percentage)", "Time in Contact with Wall (in seconds)")
names(NamesIV) <- c("ToT", "ConWall", "TimeWall", "SecondsWall")</pre>
SecondsWall <- T_M_4 %>% filter(IV == "Trial" | IV == "Intercept") %>%
 select(-lower, -upper) %>%
 pivot_wider(names_from = IV, values_from = center) %>%
 slice(rep(1:n(), each = 5)) %>%
 group_by(Proficiency, DV) %>%
 mutate(x = 1:5)
```

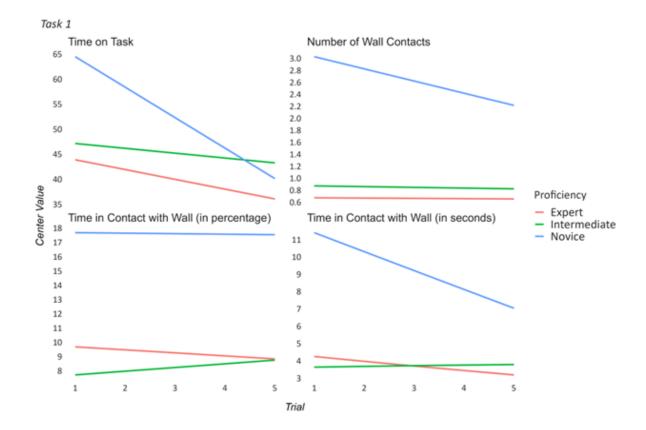
y = if\_else(DV != "ToT", Intercept + (Intercept \* Trial - Interce

pt) \* x, Intercept + Trial \* x)) %>%

```
74
```

```
ungroup() %>%
 select(-Trial, -Intercept) %>%
 pivot_wider(names_from = DV, values_from = y) %>%
 mutate(SecondsWall = ToT * (TimeWall/100)) %>%
 pivot_longer(c(ToT, ConWall, TimeWall, SecondsWall), names_to = "IV") %>
%
 mutate(IV = factor(IV, levels = c("ToT", "ConWall", "TimeWall", "Seconds
Wall"))) %>%
 ggplot(aes(x = x, y = value, color = Proficiency)) +
 geom line(size = 1.2) +
 scale_y_continuous(breaks = scales::pretty_breaks(n = 10)) +
 #facet_wrap("Measure", scales = "free") +
 xlab("Trial") +
 ylab("Center Value") +
 labs(title = "Task 1") +
 facet_wrap("IV", scales = "free_y",
 labeller = labeller(IV = NamesIV)) +
 bbc_style_R()
finalise_plot(plot_name = SecondsWall,
 source = "",
 save_filepath = "SecondsWall.png",
 width_pixels = 1000,
 height pixels = 700)
```

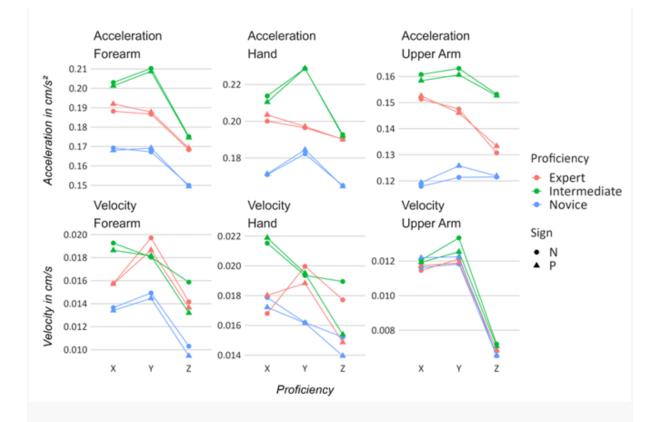
```
• • •
```



Model without or with Sign Indicator?

```
```{r}
WS_A <- brm(Acceleration \sim 0 + Proficiency:Position:Axis:Sign, data = D_2,
family = exgaussian, cores = 4, warmup = 1000, iter = 2000)
WS V <- brm(Velocity ~ 0 + Proficiency:Position:Axis:Sign, data = D 2, fam
ily = exgaussian, cores = 4, warmup = 1500, iter = 3000)
T WS A <- as.tibble(fixef(WS A)) %>%
  mutate(OutcomeVar = "Acceleration")
T WS V <- as.tibble(fixef(WS V)) %>%
  mutate(OutcomeVar = "Velocity")
T_WS <- rbind(T_WS_A, T_WS_V) %>%
  select(fixef, center, lower, upper, OutcomeVar) %>%
  separate(fixef, into = c("Proficiency", "Position", "Direction", "Sign")
) %>%
  mutate(Proficiency = gsub("Proficiency", "", Proficiency)) %>%
  mutate(Position = gsub("Position", "", Position)) %>%
mutate(Direction = gsub("Axis", "", Direction)) %>%
 mutate(Sign = gsub("Sign", "", Sign))
\sum{r}
NamesPosition <- c("Hand", "Forearm", "Upper Arm")</pre>
names(NamesPosition) <- c("Hand", "FoArm", "UpArm")</pre>
P WS <- T WS %>%
  ggplot(aes(x = Direction, y = center, color = Proficiency, shape = Sign)
) +
  geom_point(size = 3) +
  geom_line(aes(group = interaction(Sign, Proficiency))) +
  scale y continuous(breaks = scales::pretty breaks(n = 5)) +
  facet wrap(OutcomeVar ~ Position,
              labeller = labeller(Position = NamesPosition), scale = "free
y") +
  labs(x = "Proficiency", y = "Velocity in cm/s
                                                                             Ac
celeration in cm/s<sup>2</sup>") +
  bbc style R()
finalise_plot(plot_name = P_WS,
         source = "Positive and Negative Direction",
         save_filepath = "PositiveNegative.png",
         width_pixels = 900,
         height pixels = 600)
• • •
```

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```
```{r}
```

OS\_A <- brm(Acceleration ~ 0 + Proficiency:Position:Axis, data = D\_2, fami ly = exgaussian, cores = 4, warmup = 1000, iter = 2000) OS\_V <- brm(Velocity ~ 0 + Proficiency:Position:Axis, data = D\_2, family = exgaussian, cores = 4, warmup = 1000, iter = 2000) Loo\_OS\_A <- loo(WS\_A, cores = 1) Loo\_WS\_A <- loo(OS\_A, cores = 1) T\_LOO\_A <- compare\_IC(list(Loo\_OS\_A, Loo\_WS\_A)) write\_clip(T\_LOO\_A) Loo\_OS\_V <- loo(OS\_V, cores = 1) Loo\_WS\_V <- loo(WS\_V, cores = 1) T\_LOO\_V <- compare\_IC(list(Loo\_OS\_V, Loo\_WS\_V))</pre>

# Appendix E: Converting the Xsens files to a data set using Excel and R

The Xsens Motion Capture files (.mvn) are not directly suitable for performing data manipulation or data analysis. Consequently, they need to be converted to a proper format. Manually converting these Xsens files takes a lot of time and is highly error prone potentially biasing or distorting the data. Therefore, we have developed a procedure that can convert all the files at once with minimal effort by using Excel Power Query and a specified R-Script.

Note: In order to create the data set, you need to have specified the information to identify the files by either using the **Xsens comment feature** or by naming the **Xsens files**. For example, if participant 15 completed the second task for the third time during an experiment we could name the file: Par 15 - Task 2 - Trial 3. This way we can tell the script what data belongs to which participant and so on.

The following steps are necessary to create our data set:

1. First, each Xsens file needs to be converted to the Excel Workbook format (.xlsx). You can open the Xsens files (.mvnx) at once by dragging all files into an open excel document. Select the option to open the files as an XML table.

2. Next, save all open Excel workbooks as an xlsx format. You can do this by following the steps in the box below.

Press Alt + F11 simultaneously to open the Microsoft Visual Basic Application window.	
In the Microsoft Visual Basic Application window, click <b>Insert &gt; Module</b> . Then copy and paste below VBA code into the <b>Module</b> window.	
Sub SaveAll()	
Dim xWb As Workbook	
For Each xWb In Application.Workbooks	
If Not xWb.ReadOnly And Windows(xWb.Name).Visible Then	
xWb.Save	
End If	
Next	
End Sub	
Press the <b>F5</b> key to run the VBA code.	
3. Store all resulting files in the same folder.	

4. Now, we can open Excel Power Query. We can find Excel Power Query by clicking on *Data* on the top ribbon à then on *Get Data* à From File à From Folder à select the folder with the previously stored files à then select "Combine and Load"

5. Save the resulting file as an Excel Workbook file (.xlsx).

6. The rest of the data manipulation can be performed using the R-Markdown script below. You need to copy the script into an R-Markdown document and run the individual segments. The segments are accompanied by descriptions that should help to understand the rationale behind the script.

```
```{r}
library(splitstackshape)
library(dplyr)
library(readx1)
library(zoo)
```{r}
D 1 <- read excel("ExcelFileName.xlsx")</pre>
colnames(D_1) <- gsub("ns1:","", colnames(D_1))</pre>
RS = Right Shoulder,
RH = Right Hand,
RUA = Right Upper Arm,
RFA = Right Fore Arm,
RUL = Right Upper Leg,
RLL = Right Lower Leg,
RF = Right foot,
RT = Right Toe
and so on"
Xsens_Sensor <- c("Pelvis_X","Pelvis_Y", "Pelvis_Z", "T8_Y", "T8_Z", "Head
_X", "Head_Y", "Head_Z", "RS_X", "RS_Y", "RS_Z", "RUA_X", "RUA_Y", "RUA_Z"
, "RFA_X", "RFA_Y",
, "LS_Z", "LUA_X",
 "RFA_Z", "RH_X", "RH_Y"
 ', "RH_Z"
 H_Z", "LS_X", "LS_Y"
"LFA_Y", "LFA
 "RFA_X", "RFA_Y", "RFA_Z", "RH_X", "RH_Y", "RH_Z", "LS_X",
"LS_Z", "LUA_X", "LUA_Y", "LUA_Z", "LFA_X", "LFA_Y",
Z", "LH_X", "LH_Y", "LH_Z", "RUL_X", "RUL_Y", "RUL_Z", "RLL_X",
 Ζ",
 "RLL_Z", "RF_X", "RF_Y", "RF_Z", "LUL_X", "LUL_Y", "LUL_Z", "LLL_X", "L
LL_Y", "LLL_Z", "LF_X", "LF_Y", "LF_Z")
Labels if you are concerned for the sensors directly
Xsens_Segments <- c("Pelvis_X", "Pelvis_Y", "Pelvis_Z", "L5_X", "L5_Y", "L5</pre>
Z", "L3_X", "L3_Y", "L3_Z", "T12_X", "T12_Y", "T12_Z", "T8_X", "T8_Y", "
8_Z", "Neck_X", "Neck_Y", "Neck_Z", "Head_X", "Head_Y", "Head_Z", "RS_X",
"RS_Y", "RS_Z", "RUA_X", "RUA_Y", "RUA_Z", "RFA_X", "RFA_Y", "RFA_Z"
"RH_X", "RH_Y", "RH_Z", "LS_X", "LS_Y", "LS_Z", "LUA_X", "LUA_Y",
```

"LFA\_Z", "LH\_X", "LH\_Y", "LH\_Z", "LUA Z", "LFA X", "LFA Y", "R UL\_X", "RUL\_Y", "RUL\_Z", "RLL\_X", "RLL\_Y", "RLL\_Z", "RF\_X", "RF\_Y", "RF\_Z", "RT\_X", "RT\_Y", "RT\_Z", "LUL\_X", "LUL\_Y", "LUL\_Z", "LUL\_X", "LUL\_Y", "LL L\_Z", "LF\_X", "LF\_Y", "LF\_Z", "LT\_X", "LT\_Y", "LT\_Z")

## Labels if you look at the body segments

"RLL Y

"Т

"RFA\_Z",

```
```{r}
D_2 <- D_1 %>%
```

```
select(Source.Name, comment, time, index, marker, ## select "Identifier
Variables"
         orientation, position, velocity, acceleration, sensorFreeAccelera
tion, sensorOrientation) %>% ## select Movement Parameters
  separate(comment, into = c("Task", "Trial"), sep = "-") %>% ## "comment"
= the comment that you can give in the Xsens software after finishing the
recording
  separate(Source.Name, into = c("Participant", "TrialNumber"), sep = ",")
%>% ## "Source.Name" = the file name
  select(-TrialNumber) %>%
  mutate(Participant = gsub("Par", "", Participant)) %>%
mutate(Task = gsub("Task ", "", Task)) %>%
mutate(Task = gsub(" ", "", "Task")) %>%
  mutate(Task = gsub(" ", ", "Task")) %>%
mutate(Trial = gsub(" Trial ", "", Trial)) %>%
mutate(marker = gsub("Marker_", "", marker)) %>% ## gets rid of all the
strings so that we are left with numerical descriptions
  mutate(marker = as.numeric(marker)) %>%
  na.locf(.,fromLast=TRUE) %>%
  group_by(Participant, Trial, Task) %>% ## filters the range between the
first event marker and the last event marker
  filter(marker == max(marker)) %>% ## this does only work if you have exa
ctly two event markers --> if not, you need to make some adaptions to the
code
 ungroup()
```{r}
D 3 <- D 2 %>% select(-sensorFreeAcceleration, -sensorOrientation, -
position) %>%
If you look at the data set, you will see that our outcome measures are
an aggregation of values separated by spaces.
 # Each separate value within the rows represents a sensor or segment and
its direction on the X,Y,Z plane.
 # The following code separates the values and assigns them the
corresponding label.
separate(orientation, into = Xsens_Segments, sep = " ") %>%
rename_with(~paste0(., "_Orientation"), Pelvis_X:LT_Z) %>%
 separate(acceleration, into = Xsens_Segments, sep = " ") %>%
 rename_with(~paste0(., "_Acceleration"), Pelvis_X:LT_Z) %>%
```

```
separate(velocity, into = Xsens_Segments, sep = " ") %>%
```

rename\_with(~paste0(., "\_Velocity"), Pelvis\_X:LT\_Z) %>%
## The code above adds names to our columns (E.g "\_Velocity") starting
from the column named Pelvis\_X up until the column LF\_Z.
## Note that the name of the last label changes depending on whether we
use Xsens\_Segments or Xsens\_Sensor. For Xsens\_Sensor, you need to use
Pelvis\_X:LF\_Z

### Appendix F: Matlab Syntax: Synchronize OBS Video Recordings and Xsens

The following Syntax can be used to Synchronize Xsens and OBS by letting the Syntax perform keyboard and mouse actions close to simultaneously.

```
Set before running the main Syntax
taskNumber = 0; % reflects the number of the task the user is currently
% % performing
```

Main Syntax:

(The individual functions are defined below)

```
if taskNumber == 0
 StartRecord_Reframe();
 taskNumber = taskNumber +1;
%tap into Xsens, reset position, set marker and starts the OBS recording
elseif taskNumber == 1 || taskNumber == 3 || taskNumber == 5 || taskNumber ==
7
 taskNumber = taskNumber +1;
 XsensSetMarkerStop();
%sets a marker in Xsens
elseif taskNumber == 2 || taskNumber == 4 || taskNumber == 6 || taskNumber ==
8
 taskNumber = taskNumber +1;
 XsensSetMarkerStart();
%sets a marker in Xsens
elseif taskNumber == 9 %all the tasks should be finished at this point
 StopRecord();
 taskNumber = taskNumber + 1;
 %stops recording of OBS and Xsens
```

end

#### StartRecord\_Reframe:

```
import java.awt.Robot
import java.awt.event.*
robot = Robot();
robot.mouseMove(800,700);
robot.mousePress(InputEvent.BUTTON1_MASK);
 % Move mouse to Xsens Window
robot.mouseRelease(InputEvent.BUTTON1_MASK);
robot.keyPress(KeyEvent.VK_CONTROL);
robot.keyPress(KeyEvent.VK_R);
 %Xsens Start Recording
pause(0.1)
robot.keyRelease(KeyEvent.VK CONTROL);
robot.keyRelease(KeyEvent.VK R);
robot.keyPress(KeyEvent.VK_CONTROL);
robot.keyPress(KeyEvent.VK_0);
 %Xsens Reset Position
pause(0.1)
robot.keyRelease(KeyEvent.VK_CONTROL);
robot.keyRelease(KeyEvent.VK_0);
pause(0.01)
```

robot.keyPress(KeyEvent.VK\_SPACE);
robot.keyRelease(KeyEvent.VK\_SPACE);

%Xsens Set Marker

%OBS Start Recording

robot.mouseMove(1600,130); robot.mousePress(InputEvent.BUTTON1\_MASK); robot.mouseRelease(InputEvent.BUTTON1\_MASK); robot.keyPress(KeyEvent.VK\_U); robot.keyRelease(KeyEvent.VK\_U);

robot.mouseMove(-1000,300);

#### XsensSetMarkerStop:

```
import java.awt.Robot
import java.awt.event.*
```

```
robot = Robot();
```

```
robot.mouseMove(800,700)
robot.mousePress(InputEvent.BUTTON1_MASK);
robot.mouseRelease(InputEvent.BUTTON1_MASK);
```

```
robot.keyPress(KeyEvent.VK_SPACE);
```

robot.keyPress(KeyEvent.VK\_CONTROL);

robot.keyRelease(KeyEvent.VK\_CONTROL);

robot.keyPress(KeyEvent.VK\_R);

robot.keyRelease(KeyEvent.VK\_R);

robot.mouseMove(1000,700);

%Xsens Window

%Xsens Marker

%Xsens Recording

#### **XsensSetMarkerStart**

pause(0.1)

<pre>import java.awt.Robot import java.awt.event.*</pre>		
<pre>robot = Robot();</pre>		
<pre>robot.mouseMove(600,300) robot.mousePress(InputEvent.BUTTON1_MASK); robot.mouseRelease(InputEvent.BUTTON1_MASK);</pre>	%Xsens Window	
<pre>robot.keyPress(KeyEvent.VK_CONTROL); robot.keyPress(KeyEvent.VK_R); pause(0.1) robot.keyRelease(KeyEvent.VK_CONTROL); robot.keyRelease(KeyEvent.VK_R);</pre>	%Xsens Recording	
<pre>robot.keyPress(KeyEvent.VK_CONTROL); robot.keyPress(KeyEvent.VK_0); pause(0.1) robot.keyRelease(KeyEvent.VK_CONTROL); robot.keyRelease(KeyEvent.VK_0);</pre>	%Xsens Reframing	
<pre>robot.keyPress(KeyEvent.VK_SPACE); robot.keyRelease(KeyEvent.VK_SPACE);</pre>	%Xsens Marker	

robot.mouseMove(-1000,300);
%moves the mouse back on the screen with MATLAB running

#### StopRecord

```
import java.awt.Robot
import java.awt.event.*
```

```
robot.mouseMove(800,700);
robot.mousePress(InputEvent.BUTTON1_MASK);
 %Xsens Window
robot.mouseRelease(InputEvent.BUTTON1_MASK);
 %Xsens Marker
robot.keyPress(KeyEvent.VK_SPACE);
robot.keyRelease(KeyEvent.VK_SPACE);
robot.keyPress(KeyEvent.VK_CONTROL);
 %Xsens Record
robot.keyPress(KeyEvent.VK_R);
pause(0.1)
robot.keyRelease(KeyEvent.VK_CONTROL);
robot.keyRelease(KeyEvent.VK_R);
robot.mouseMove(1600,730);
 %OBS Record
robot.mousePress(InputEvent.BUTTON1_MASK);
robot.mouseRelease(InputEvent.BUTTON1_MASK);
pause(0.1)
```

```
robot.mouseMove(-1000,300);
```

robot.keyPress(KeyEvent.VK\_U); robot.keyRelease(KeyEvent.VK\_U);

# **Appendix G: 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

Α	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 <b>not</b> 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.: Gerret-senE). 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 Manier
	nipulation and Task 3 – Lung Anatomy, Bronchial Segments.
4	Open the Xsens backpack and place the necessary velcro tapes, t-shirts, head- bands and gloves on the desk.
В	Welcome the participant
1	Greet Participant in front of the room. Introduce yourself and let them store their be- longings on the table next to the simulator but remind them to bring their water bot- tle/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)
С	Preparation of the participant and MVN gear.

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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 sen- sors 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.
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 broncho- scope 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 move- ments 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
	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 <b>not</b> 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) → Run Myo Script (Section: Stop and Start Streaming)             START (participant passes the start line) → Run Myo Script (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 <b>picture</b> from the simulator metrics that appear on the bottom right of the screen.
9	(The MVN Recording will be stopped automatically) $\rightarrow$ 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 <b>picture</b> from the simulator metrics that appear on the lower right of the screen.
11	(The MVN Recording will be stopped automatically) $\rightarrow$ 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 <b>picture</b> from the simulator metrics that appear on the lower right of the screen.
13	(The MVN Recording will be stopped automatically) $\rightarrow$ 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 <b>picture</b> from the simulator metrics that appear on the lower right of the screen.
15	(The MVN Recording will be stopped automatically) $\rightarrow$ 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 <b>picture</b> 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 con- nection to Myo)
19	(5 minute break.) (The MVN Recording will be stopped automatically) $\rightarrow$ 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 <b>Yes</b> 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 <b>No</b> 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.
22 23	
	file corresponding to Task 3.
	file corresponding to Task 3. 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 <b>Yes</b> when "Do you
23	file corresponding to Task 3. 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 <b>Yes</b> when "Do you want to save performance?" appears on the screen. (The MVN Recording will be stopped automatically) → Save File with Comment
23 24	file corresponding to Task 3. 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 <b>Yes</b> when "Do you want to save performance?" appears on the screen. (The MVN Recording will be stopped automatically) → Save File with Comment Task 3 Trial 1.
23 24	<ul> <li>file corresponding to Task 3.</li> <li>Start Task 3 Trial 1 - Run Myo Script (Section: Stop and Start Streaming).</li> <li>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.</li> <li>(The MVN Recording will be stopped automatically) → Save File with Comment Task 3 Trial 1.</li> <li>Start Task 3 Trial 2 - Run Myo Script (Section: Stop and Start Streaming).</li> <li>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</li> </ul>

	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 <b>Yes</b> 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) $\rightarrow$ 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 <b>.zip</b> .
5	To turn off the simulator, click "Logout", "Shut down" and press the "ON/OFF" switch