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Investigating Bimanual Haptic Exploration With Arm-Support Exoskeletons

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INVESTIGATING BIMANUAL HAPTIC EXPLORATION WITH ARM-SUPPORT EXOSKELETONS

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ABSTRACT

The ability to judge properties like weight and length of hand-held objects is essential in industrial work. Sometimes workers use devices like exoskeletons, which can augment their ability to lift and move heavy objects. Previous studies have investigated the perceptual information available for one-handed weight and length judgments. The current study investigated how blindfolded participants bimanually heft and wield objects to explore haptic information, to perceive object heaviness or length. The study also investigated the effects of using an arm-support exoskeleton (ASE) on the perceived weight of hand-held objects. We empirically tested whether people wield and manipulate objects differently, depending on whether they are asked to report the perceived weight or length of objects. Participants were presented with a rod, with weights attached either symmetrically on both sides of the center, or asymmetrically on one side. In Experiment 1, blindfolded participants were asked to either judge the weight or the length of a set of rods, after they actively wielded each rod. In Experiment 2, a different group of participants wearing an ASE to support lifting objects above shoulder level reported the perceived weight of the hand-held rod with their arms stretched above their shoulder level. The study has implications on designing exoskeletons, and training people to improve their weight and length judgments with and without wearing ASEs.

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TABLE OF CONTENTS

Table of Contents (Continued) Page

LIST OF FIGURES

List of Figures (Continued)

Figure Page

List of Figures (Continued)

Figure Page

CHAPTER ONE

INTRODUCTION

The environment surrounding an organism, the information available in the environment, the medium which carries the information, and the features of the organism, all play a role in how the organism behaves (Blau & Wagman, 2022; Gibson, 1979). Organisms can perceive the opportunities for action available in the environment, which Gibson (1979) termed as affordances. An organism's survival depends on how it explores the environment and orients its senses to the time invariant information available to successfully perceive affordances (Turvey et al., 1981). For example, a gannet diving into water to catch fish must perceive the time to contact with the water surface, so that it can close its wings exactly as it touches the surface. A delay in orienting its body and coordinating this action will hurt the bird. The importance of successfully perceiving affordances is not any different in humans compared to other organisms. An industrial worker who lifts and moves heavy objects as part of their job must perceive their ability to move the objects without exerting themself, to avoid musculoskeletal damage.

Information specifying affordances

> "Perception is not a response to a stimulus but an act of information pickup" – Gibson (1979, p. 50).

Humans can judge properties like the length and weight of hand-held objects even without vision. Such perception of object properties by intentionally exploring and manipulating the object is termed as dynamic or effortful touch (Carello & Turvey, 2015;

Gibson, 1966; Turvey & Carello, 2011). Understanding how humans perceive such affordances is not only helpful in designing hand-held tools like hammers, but it also contributes to designing devices and products like exoskeletons and prosthetic limbs, that can augment human capabilities (Raveendranath, Rosopa & Pagano, 2024). It can also aid in designing training programs that help people adapt to such devices and other hand-held tools. When people use such tools, task-specific, time invariant information directly specifies the affordances available. Perceiving such affordances is a lawful process, as the properties of the object being explored, and the features of the person holding the object will structure the haptic energy arrays of physical forces on the muscles, skin, and other bodily tissues (Blau & Wagman, 2022). In general, the time invariant information available in the haptic array for dynamic touch has been identified as the inertia tensor (Iij) - the resistance of an object against rotations in the different directions about an axis of rotation (Amazeen & Turvey, 1996; Carello, Santana & Burton, 1996; Pagano & Turvey, 1992; Pagano et al., 1993; Shockley et al., 2004; Solomon & Turvey, 1988). The inertia tensor is composed of the moments of inertia (Ixx, Iyy, Izz) and products of inertia (Ixy, Iyz, Ixz) components. When a person hefts and wields an object with their hand, the inertia tensor at the grasped position enables them to perceive affordances like the distance that they can reach with the object, weight of the object etc. Although initial experiments conducted to study dynamic touch were done with participants placing their forearm stationary against a table, and moving only their wrist, Pagano et al. (1993) studied dynamic touch as participants wielded objects by moving multiple joints in their arm simultaneously. It was found that participants still successfully perceived the object properties by picking up haptic information - the moment of inertia about their wrist.

Solomon & Turvey (1988) manipulated the moment of inertia at the grasped tip of rods of different lengths by attaching weights at different points on the rods. They found that although the perceived lengths of hand-held objects correlated with the actual lengths of the rods, participants detected the moment of inertia at the grasped tip to perceive the length. In other words, the moment of inertia predicted the perceived length better than the actual length of the rod. On the other hand, a study by Carello et al., (1996), showed that products of inertia and moments of inertia both played a role in identifying the partial length in front or behind the position of grasp on a hand-held object. This indicates that people perceive affordances directly by detecting the invariant information in the energy (haptic) array.

Traditional theories of weight perception discuss perceived weight to be dependent on the actual mass and size of the object, leading to a phenomenon known as the size-weight illusion. In this illusion, when two objects of the same mass, but different sizes are presented to participants, the larger object is perceived to be lighter than the smaller object (Charpentier, 1891; Dresslar, 1894). To study the affordance to perceive weights, Amazeen & Turvey (1996) used tensor objects – consisting of multiple metal rods clustered together into a movable joint that could be attached anywhere on a hand-held rod. Weights could be attached to these metal rods to manipulate the moments of inertia. In this study, it was found that perceived weight increases with increase in moments of inertia in different directions. This indicates that this affordance is perceived lawfully in terms of the moment of inertia, rather than integrating the lower order information on the size and mass of the observed object.

Exploratory movements and muscle activity

Dynamic touch has been studied traditionally in terms of neural activity, and a central executive controlling the input from the senses and providing feedback (Rosenbaum, 2009). In essence, according to the traditional approach, the function of the central executive is to control the many degrees of freedom available for moving the different parts of the body, contributing passively towards perception as well. According to the ecological approach, the brain does not have to individually control the degrees of freedom of the joints or integrate each piece of goal relevant information separately. Turvey & Fonseca (2014) hypothesized that the human musculoskeletal system is a tensegrity structure where the body itself is the medium conveying information. The muscles, tendons, skin and all the other tissues in the body are part of the perceptual system, contributing to active exploration of information in dynamic touch. There has been a lot of interest recently, not just in psychology, but also in fields like robotics, in the mechanism by which exploratory movements of the whole body contribute to revealing task specific invariant information over time (Nonaka, 2019; Yu et al., 2023).

For any organism, exploratory movements are essential to attune to task relevant information and calibrate to one's own action capabilities. Prior studies have inspected such exploratory behavior in terms of fluctuations and long-range correlations in movement pattern (Stephen et al., 2010; Nonaka & Bril, 2014), and the recurring patterns in the phase space of hand movements (Riley et al., 2002). In a study by Stephen et al.

(2010), blind-folded participants were asked to judge the affordance of reaching with a hand-held object and measured their exploratory wielding movements. It was found that movement fluctuations had long-range temporal correlations, with systematically larger fluctuations at longer time scales and smaller fluctuations at shorter time scales. That is, movement fluctuations were geared towards attuning to the task relevant invariant information was possible. Similarly, Nonaka & Bril (2014) studied the exploratory tapping movements made by stone craftsmen in India, where it was found that expert craftsmen showed increased long-range correlations in exploratory movement patterns when presented with novel conditions, as compared to novices who showed significantly lower long-range correlations. Similar findings were also reported by Mangalam et al. (2020), who found that participants' center of pressure displacement showed long-range correlations as they hefted and wielded different rods to perceive its weights and lengths. In general, these studies show that exploratory movements can indicate the skill level of the explorer, as well as whether they are learning to calibrate to the relevant information over time.

Previous studies uncovered how the intention to perceive different properties of an object lifted with one hand affects how people wield the object and seek information through dynamic touch (Arzamarski et al., 2010; Riley et al., 2002). In other words, a person who intends to perceive the length of a rod would exhibit a different exploratory behavior (heft and wield the rod differently) as compared to when they intend to perceive its width. This is referred to as the co-specificity hypothesis, which ties together an organism's intention, exploration, and the information that specifies the property that the organism intends to perceive (Arzamarski et al., 2010; Riley et al., 2002). These studies found that the principal moment of inertia, Ixx, was correlated with participants' report of perceived length, while they tapped into Izz to perceive the width of the wielded object.

Studies have also explored whether muscle activity measured using electromyography (EMG) contributes towards perceived weight and length of hand-held objects. Mangalam et al., (2019) found that fluctuations in EMG activity were different when people intended to perceive the length of a rod as compared to its heaviness. In general, it has been found that muscular activity in the biceps brachii, flexor carpi radialis, and flexor carpi ulnaris muscles contribute towards perceiving the weight of hand-held objects, while perceived length was weakly related to the activity of biceps brachii (Mangalam et al., 2019; Waddell et al., 2016). Similarly, Waddell and Amazeen (2017) studied the role played by muscle activity and joint kinematics in perceiving the weight of rods by following unimanual lifting procedures about the shoulder, elbow, or wrist. Such relation between muscle activity and/or kinematics, and perceived weight or length of objects has been explored not just for lifting objects using the upper body, but also about segments of the body, like the legs, or shoulders (Palatinus, Carello & Turvey, 2011; Waddell & Amazeen; 2018). Interestingly, people can perceive the length of held objects even in the case of quiet standing, without active exploratory movements (Palatinus et al., 2014). In this study, subtle differences in postural fluctuations were observed as participants tried to perceive the length of the whole rod, as compared to its partial length. Given our ability to explore, even if our goals or action capabilities change, or if the perceptual information changes because of a change in environmental factors, we can still recalibrate easily, thereby improving our performance. The pattern of our movements and muscle activity will also change as part of this process.

Studies have also found that regardless of whether a hand-held object is wielded in air or water, participants pick up the moment of inertia to perceive the object length (Mangalam et al., 2017; Pagano & Cabe, 2003; Pagano & Donahue, 1999). The drag (resistance exerted by a fluid stream on an object moving through the fluid) associated with water is much greater than that associated with air. Therefore, the torque required to wield an object in water is much greater, indicating that more muscle activity is required to heft and wield objects in water as compared to air. Since perceived length is invariant across the medium in which an object is wielded, muscle activity might not play a role in length perception as much as it does in weight perception. However, there are tasks where non-specifying variables, like the drag associated with the medium, could play a role in the perception of affordances. For example, in a simulated laparoscopic surgery task, Altenhoff et al. (2017) found that participants were much worse at picking up the invariant information to perceive the distance to break a tissue, when friction (a non-specifying variable similar to drag in the medium in dynamic touch) was absent in the interface. This indicates that friction might have invoked more muscle activity and played a role in helping the participants to perceive the affordance of distance to break tissue. When people wear an ASE, it is possible that it reduces their muscle activity, which otherwise plays a significant role in weight perception. Moreover, in a recent study, Raveendranath, Pagano & Srinivasan (2024) found that ASEs can affect the wearer’s movements in repetitive pointing tasks above the shoulder level. Therefore, with reduced muscle activity and restricted movements, one could expect more errors in the judgment of perceived weight when people wear an ASE.

Attunement and calibration

In general, exploration of information, attunement and calibration are identified as three main aspects of perceptual learning while interacting with hand-held objects (Wagman et al., 2001). Thus, while using a hand-held object, the user is learning to explore the inertia tensor and attune to the goal relevant invariant information available. After getting attuned to the relevant information, one perceives such hand-held objects to be a part of their own body. In other words, the tool becomes a part of the user's body schema (Day et al., 2019; Venkatakrishnan et al., 2023). While using a hand-held object, new possibilities of actions become revealed to the user. The perception of these affordances requires the user to scale the available information to their own action capabilities.

When baseball batters warm up before games, sometimes they add some extra weight to their bats. This increases the inertia of the bat. To attune to this increased inertia of the bat, the batter now produces a large amount of force in their muscles. Following this routine, when they remove the weight and bat during the game, it helps them generate a large amount of force to hit the ball farther. However, this could affect the timing of their swing, since sometimes they end up swinging the bat faster than they are used to. In a study done by Scott & Gray (2010), when the participants used a lighter or a heavier bat, it took them around 5 or 10 attempts respectively, to get adapted to the change in bat weight, for any significant changes in their hitting performance to disappear. When the batters were allowed to wield and dynamically explore the bat in their hands (without swinging it) before hitting, the number of attempts required to calibrate reduced significantly. It was also noted that participants used one of two strategies to swing the bat and perform better, depending on their action capabilities. Participants who were comfortable enough to swing a heavier bat calibrated by adjusting their swing velocity. They were able to swing the bat harder and generate more force. Those who were not comfortable using a heavier bat calibrated by adjusting the timing of their swing, rather than their swing velocity.

Bimanual lift

Most of the research discussed so far on dynamic touch focuses on wielding objects with one hand before making judgments about the object properties like length and weight. Although sometimes we use one hand to lift tools and other objects, we tend to use both our hands for many tasks, and still accurately perceive the length and weight of the wielded object. Many of the studies on weight and length perception via bimanual lifts have investigated precision grasps, rather than dynamic (effortful) touch that was discussed so far (Ganel, Namdar & Mirsky, 2017; Giachritsis et al., 2009; Giachritsis et al., 2010; Lopes et al., 2017; Panday et al., 2014). In such tasks, either force feedback haptic interfaces or real objects are used to manipulate grasps. Participants mostly use their fingers or the palm to make their estimations of the object's properties or force feedback. There are also studies where participants make judgments of object weight by grasping the object using just the index finger and thumb and repeating this with both their hands separately (van Polanen, 2022). In general, objects held bimanually are considered to require less effort and feel lighter, as compared to objects held unimanually (Lim et al., 2021).

Some studies on weight perception via bimanual lifts have been done in the context of manual material handling and maximum acceptable weight of lifting (Banks & Caldwell, 2019; Lee & Cheng, 2011). Although such studies involve bimanual lifting tasks, they focus on the acceptable weight that the participants can lift over a scheduled period, rather than on the mechanisms based on which they perceive such weight. Research investigating maximum acceptable weight of lifting generally manipulates object features that might affect the maximum acceptable weight, such as, object size, frequency of lift, the symmetry of distribution of weight on the object being handled, symmetry of trunk bending etc. (Abadi et al., 2015; Lee & Cheng, 2011; Mital & Fard, 1986; Mital & Manivasagan, 1983).

Arm Support Exoskeletons

Exoskeletons are wearable devices that support or augment users' physical abilities. They reduce the physical demands of repetitive tasks involving heavy material handling, work performed with arms elevated, the use of heavy tools, etc. Exoskeletons could be either active or passive. Active exoskeletons are driven by motors, pneumatic systems, or hydraulic systems, while passive exoskeletons use elastic materials to store and release energy during lifting tasks. Exoskeletons could also be classified based on the part of the body that they support. For example, back-support exoskeletons are expected to reduce the risks of occupational low-back injuries while performing jobs involving manual material lifting, shoveling etc. Upper-limb exoskeletons, also known as ASEs are used in overhead assembly and overhead lifting to prevent injuries to the shoulder and arms. Some studies using such exoskeletons have focused on precision tasks. For example, Madinei et al. (2020) designed a task where participants wearing a back-support exoskeleton were asked to pick up pegs from a pegboard and accurately place them on grooves. In the experiment by Kelson et al. (2019), participants wearing an ASE repeatedly pointed towards target points at different distances while holding a hand drill. Similarly, Kim et al. (2021) performed a field study at an automotive assembly facility where the workers performed precision assembly tasks.

Prior studies on bimanual lifts using exoskeletons have been done using passive ASEs as well as back-support exoskeletons (Alemi et al., 2020; Gillette & Stephenson, 2018; Madinei et al., 2020; Smets, 2018). In such studies, participants are usually asked to repeatedly lift and lower objects which weigh a small percentage of their body mass. Since exoskeletons are expected to reduce stress on muscles, many of these experiments measure and investigate muscle activity during the task. For example, studies indicate that depending on the task, ASEs can significantly reduce muscle activity in the anterior deltoid, biceps brachii and trapezius muscles (Gillette & Stephenson, 2018).

Using exoskeletons in industrial work has some limitations as well. Smets (2018) points out that although many workers suggested using exoskeletons to other workers performing overhead work, some of them expressed concerns about exoskeletons hindering job execution. Workers stated that wearing ASEs would restrict movement in tight spaces, and while sitting and bending over. Kim et al. (2021) also note that restricted joint movements, elevated contact pressure, and altered working postures could be some issues that might arise as industrial workers start using exoskeletons. Although most of the studies discussed in this section focus on the effect of exoskeletons on industrial work, and how it can reduce musculoskeletal damage, the possible impact that exoskeletons could have on perceiving hand-held object properties has not been studied so far.

Present study

This project investigated whether blindfolded participants can accurately judge the weight and length of hand-held objects by hefting and wielding them bimanually, with or without wearing an ASE. Since almost all the previous studies on dynamic touch investigated unimanual wielding, experiment 1 was designed to understand how people perceived the weight and length of rods through bimanual wielding. Experiment 2 was designed to understand how people perceived the weight of hand-held rods as they wore an ASE.

In both the experiments, the blindfolded participants were presented with a wooden rod with 453.6 g (1 lb.), 907.2 g (2 lbs.), or 1360.8 g (3 lbs.) weights distributed either symmetrically on both sides of the center of the rod, or asymmetrically biased towards the right side. In both these cases, the weights were placed at one of two distances from the gripping point – either 10 cm or 20 cm away from the hands. Participants grasped the rod using both their hands around the center, to heft and wield the rod. Participants' muscle activity was measured using surface EMG, and their movements were tracked using an inertial motion tracking system.

Understanding the mechanisms of weight and length perception in two-handed lifts has implications on designing occupational and leisure activities where manual material handling is common. Furthermore, by incorporating a deeper understanding of the mechanisms by which users' bodies acquire and use information about hand-held objects, the results of this study can guide the design of exoskeletons.

CHAPTER TWO

EXPERIMENT 1

Experiment 1 investigated participants' exploratory movements and EMG activity as they wielded rods bimanually. Participants held the rod with their forearms extended parallel to the ground. One goal of this experiment was to understand whether the participants' intention to perceive the weight or length of the rod affected their exploratory hefting and wielding movements. Further, the study also explored whether weight and length perception are affected by the symmetrical or asymmetrical distribution of weights on the rod, and how far away from the grip the weights are attached.

Hypotheses

Based upon the previous research discussed in chapter 1, the hypotheses for experiment 1 are as below:

H1: When the weight is distributed asymmetrically, perceived heaviness and length will increase as compared to when weight is distributed symmetrically.

H2: When weights are placed farther from the grip position, perceived heaviness and length will increase as compared to when weights are placed closer to the grip position.

H3: When the magnitude of weight attached to the rods increases, perceived heaviness and length will increase.

H4: The dynamics of muscle activity will be different when participants intend to perceive the weight of a rod, as compared to its length.

H5: The dynamics of muscle activity will be more periodic and stable when participants wield rods with weights distributed symmetrically as compared to asymmetrically.

H6: The dynamics of muscle activity will be more periodic and stable when participants wield rods with weights attached closer to the gripped position.

H7: The dynamics of muscle activity will become less periodic and less stable when the magnitude of the weight attached to the rod increases.

H8: The dynamics of the movements of the segments of the upper body will be different when participants intend to perceive the weight of a rod, as compared to its length.

H9: When weights are distributed asymmetrically, perceived heaviness will show a strong relationship with the ratio of EMG activity to lifting acceleration for the biceps brachii, flexor carpi radialis, and flexor carpi ulnaris for the hand that is closer to the weight, and a weak relationship with the other hand.

H10: When weights are distributed symmetrically, perceived heaviness will show a linear relationship with the ratio of EMG activity to lifting acceleration for the biceps brachii, flexor carpi radialis, and flexor carpi ulnaris for both the hands.

H11: Perceived length will not show a relationship with the EMG activity of the muscles, neither in symmetrical nor asymmetrical conditions.

Method

Participants

The *simr* package in R was used to determine the number of participants needed for this study (Green & MacLeod, 2016). The power analysis was conducted on the data from four pilot participants. First, linear mixed-effects models were created for each dependent variable. These models included the fixed effect of each independent variable, and a random effect of the pilot participant ID. The *powerCurve* function in *simr* was used to perform power analysis over a range of different sample sizes, by running 100 simulations. This analysis revealed that a sample size of 16, with each participant completing 60 trials for each perceptual intent was required to obtain a power above 0.8.

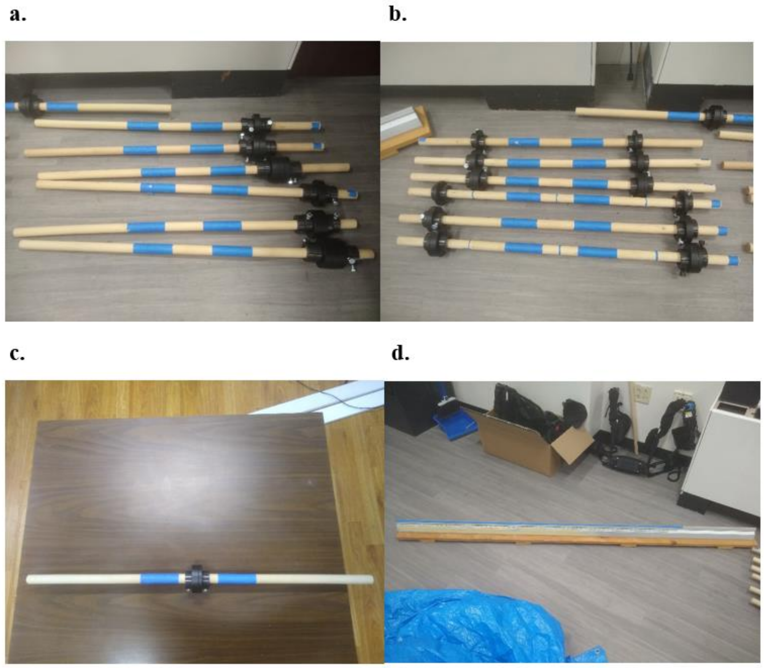
Sixteen Clemson University students participated in the study for partial course credit, or for a $30 gift card, after providing informed consent (9 females, age *M* = 19.94, *SD* = 2.35). Participants did not have any self-reported musculoskeletal injuries within 12 months prior to participation. The study was performed with approval of the Institutional Review Board of Clemson University.

Apparatus and material

Thirteen wooden rods, each measuring 36 inches (91.4 cm) in length, weighing 1 lb., and having a diameter of 1 inch (2.5 cm), were used for the experiment. Another wooden rod, 48 inches long, was shown to the participants as a sample rod prior to the experiment. Alloy steel weight plates (1 lb., 2 lbs., and 3 lbs.) with 1 inch center hole were attached to the rods either symmetrically about the center, or asymmetrically. Shaft collars were utilized for securing the weight plates onto the rods. In the symmetrical condition, the weight was evenly distributed between both sides. Blue tape was applied to each rod on either side of the center to provide a consistent gripping point for participants. The weight plates were attached either 10 cm or 20 cm away from the end of the blue tape in both the symmetrical and asymmetrical conditions (Figure 1.1 a and 1.1 b). For the weight perception task, a reference rod of the same length and mass as the experimental rods, with a 1.5 lb. weight plate attached at the center, was used (Figure 1.1 c). For the length perception task, a wooden block featuring a centimeter scale on one side was used (Figure 1.1 d). The participants were blindfolded throughout the experiment, so that they could not see the rods at any point. The total weight of the reference rod, including the weight plates, shaft collar and screws was 3.3 lbs. The total weight of the rods with 1 lb., 2 lbs. and 3 lbs. weights attached were 3.6 lbs., 4.6 lbs., and 5.6 lbs. respectively.

Figure 1.1

Thirteen wooden rods with weights attached. a) Symmetric weight distribution, b) Asymmetric weight distribution, c) The reference rod used for the weight perception task, d) The scale used for the length perception task.



On each trial, participants' whole-body kinematics were captured at 60 Hz using an inertial motion capture system (Xsens Technologies, B.V., Netherlands, MTw Awinda) (Schepers, Giuberti & Bellusci, 2018). Their muscle activity was recorded at 1.5 kHz using a surface EMG system ((Ultium™, Noraxon, AZ, USA). Raw EMG signals were recorded for the upper trapezius, anterior deltoid, biceps brachii, flexor carpi radialis and flexor carpi ulnaris on both the left and right sides of the body.

Procedure and experimental design

The electrode and sensor placements for EMG were performed following standard guidelines (Criswell, 2010). For each participant, the electrode placement point for upper trapezius was located 2 cm lateral from the midpoint on the line from the acromion to the spine on vertebra C7 (Mathiassen et al., 1995). For the anterior deltoid, the electrode was placed 4 cm below the clavicle, parallel to the muscle fibers at an oblique angle to the arm (Chopp et al., 2010). For the biceps brachii, the electrode was placed on the line between the medial acromion and the fossa cubit at 1/3 from the fossa cubit as per recommendations of SENIAM (Surface Electromyography for Non-Invasive Assessment of Muscles) (Hermens et al., 2000). The electrode placement point for flexor carpi radialis was located at 2 cm medial from the bicep tendon at the elbow crease level, to the proximal one-third of the forearm length, in the direction of the second metacarpal bone (Ahn et al., 2021; Criswell, 2010). Flexor carpi ulnaris was localized two fingerbreadths volar to ulna at the junction of the upper and middle thirds of the forearm (Lung & Siwiec, 2023; Yaşar et al., 2016). Prior to applying electrodes to the desired area, it is important to minimize skin impedance by eliminating oils and dead skin cells. To do this, a small area on the skin over the muscles where electrodes were to be attached was shaved, abraded with fine grit sandpaper, and cleaned with alcohol wipe.

After applying electrodes to the desired areas, maximum voluntary contraction (MVC) procedure was completed twice for each muscle for 5 seconds each. Participants sat upright on a chair and performed separate flexion and abduction/adduction movements for each muscle. For the upper trapezius, participants maintained their arm at 90° abduction on the frontal plane, with hand facing down and the neck in neutral position, while manual resistance was applied downward, proximal to the elbow (Mathiassen et al., 1995). For the anterior deltoid, participants elevated their shoulders to 90° in the plane of the scapula (30 to 40° from the sagittal plane), with manual resistance applied proximal to the elbow in a downward direction (Ebaugh et al., 2005). For the biceps brachii, participants had their elbow flexed at 90° and forearm supinated, while manual resistance was administered at the wrist (Roman-Liu & Bartuzi, 2018). For the flexor carpi radialis, participants performed wrist flexion and abduction, while for flexor carpi ulnaris, they performed wrist flexion with adduction, as manual resistance was applied to the wrist (Fagarasanu, Kumar & Narayan, 2004).

After completing the MVC procedure, 17 motion trackers were attached to the participants' feet, lower and upper parts of the legs, forearms, hands, upper arms, shoulders, pelvis, sternum, and the head. A sensor-to-segment calibration was performed as recommended by Schepers et al. (2018), which created a biomechanical model of the participant on the Xsens MVN software.

The experiment had two blocks of trials: one where participants reported the perceived weight of the rod, and another where they reported the perceived length. These trial blocks were counterbalanced across participants. Participants were instructed to stretch their forearm forward, parallel to the ground, with their palms facing upward before the start of each trial. They grasped the rod with their hands on both sides of the center. They were allowed to freely heft and wield the rod (Figure 1.2 a).

For the weight perception task, participants were given the reference rod every three trials. They were told that it weighs an arbitrary value of 100. Throughout the task, participants judged the weight of different rods given to them with reference to 100. The exact instruction given to the participants was "Consider this reference rod has a weight of 100. If an object weighs half as much, you should rate it as 50, while an object weighing twice as much should be rated as 200".

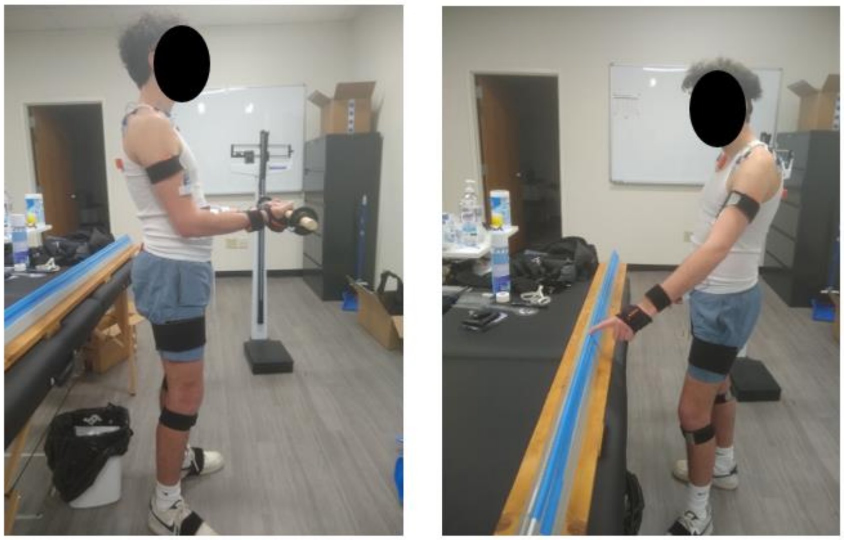
For the length perception task, after hefting and wielding the rod, participants turned around, pulled up their blindfold and indicated the perceived length of the rod on a scale placed on a table behind them (Figure 1.2 b). They were instructed to imagine one end of the rod they held aligning with the rightmost end of the scale and then indicate where they perceived the other end of the rod to be.

A within-subjects design was followed in this experiment, with participants completing trials under 2 perceptual intents (weight or length), each of which included 2 weight distributions (symmetric or asymmetric), 2 weight positions (10 cm or 20 cm from the grip position) and 3 different weight magnitudes (1 lb., 2 lbs., 3 lbs.) repeated for 5 times, resulting in a total of 120 trials per participant. On average, participants wielded the rods for 6.73 seconds in each trial. Each experimental session lasted approximately 2.5 hours.

Figure 1.2

The experimental task. a) Participant wielding the rod, b) Length judgment made by the participant,

a. b.



<u>*Data preparation*</u>

For each trial, the raw EMG signal for each muscle channel was band-pass filtered (20-450 Hz, 4th-order Butterworth, bidirectional). Following this, the root mean square (RMS) envelope for each signal was computed using a sliding window of 200 ms. A normalized EMG timeseries (with values ranging from 0-100%) was then calculated for each muscle using the corresponding maximum EMG activity recorded during the MVC procedure. Using these normalized EMG signals, the peak EMG activity for each trial was computed for further analysis.

The Xsens MVN software (MVN version 2022.0.0) generates data for joint angles, position of each segment of the body, velocity, etc. by using a biomechanical model (Schepers et al., 2018). For this study, angular acceleration for each segment of the upper body was obtained. This included the angular acceleration for the head, and bilateral measures for the shoulders, upper arm, forearm, and hands. The MVN software provides 3-dimensional vectors for the angular acceleration of the origin of each body segment in the global frame (Xsens Knowledge Base, 2023, April 5). For each upper body segment, the magnitude of angular acceleration at each time step was calculated using the formula below.

$$\alpha_{mag} = \sqrt{(\alpha_x^2 + \alpha_y^2 + \alpha_z^2)} \quad (1)$$

Using these time series of magnitude scores of angular accelerations, a peak angular acceleration score was computed for each upper body segment for each trial. The ratio of peak muscle activity to peak angular acceleration was computed by dividing the peak normalized EMG by the peak angular acceleration for the corresponding body segment responsible for contracting the muscle. When analyzing the bicep brachii, the ratio of its peak EMG to the peak angular acceleration of the forearm was computed for each trial. For flexor carpi radialis and ulnaris, the peak angular acceleration of the corresponding hand segment was used. For the upper trapezius and anterior deltoid, the peak angular acceleration of the corresponding upper arm was used.

Multidimensional Recurrence Quantification Analysis (MdRQA)

MdRQA is a nonlinear analysis technique used for multidimensional time series data to quantify recurring patterns that occur at all possible lags of time given the length of the time series (Wallot, Roepstorff & Mønster, 2016). Although MdRQA has been primarily used to study inter-personal synchronization (Baranowski-Pinto et al., 2022; Tomashin et al., 2022), there are studies that explore intra-individual multi-muscle synergies as well (Li et al., 2020). In the current study, MdRQA was first used to evaluate the recurring patterns in the normalized EMG for ten muscles on the upper body while participants performed the weight and length perception tasks. It was also used to evaluate the dynamics of angular acceleration of nine segments of the upper body. Since the EMG data was normalized, it did not have to be rescaled for the MdRQA analysis. However, the angular acceleration time series were rescaled to z-scores before performing MdRQA on these.

For each MdRQA analysis, a phase space of the multidimensional time series was reconstructed using the method of time-delayed embedding (Takens, 1981). To determine an appropriate delay, the Average Mutual Information (AMI) was calculated over increasing time lags for each time series obtained from a trial. The time lag where the first local minimum (the point where the time series reveal an optimum amount of unique information) appeared was chosen for each time series. The average of these time lag values was used as a parameter for the phase space reconstruction. The embedding dimension was determined for each time series by the first local minimum of False Nearest Neighbors (FNN; cf., Riley et al., 1999). The maximum dimension among the dimensions computed for all the time series was selected as the embedding dimension parameter for the phase space reconstruction. The radius (the area in the phase space where the revisiting trajectories are considered to be recurrent) was allowed to vary within the set of time series, so that the recurrence rate was exactly 5% (cf. Wijnants et al., 2009). These computed lag, dimension and radius were used to optimize the reconstruction for every set of time series. The recurring patterns in a set of time series can be represented on a multidimensional recurrence plot (MdRP) by charting points where the coordinates of the time series repeat in the phase space (Figures 1.3a, 1.4a, 1.5a and 1.6a). The following are the relevant measures obtained from the MdRQA for each trial in this experiment:

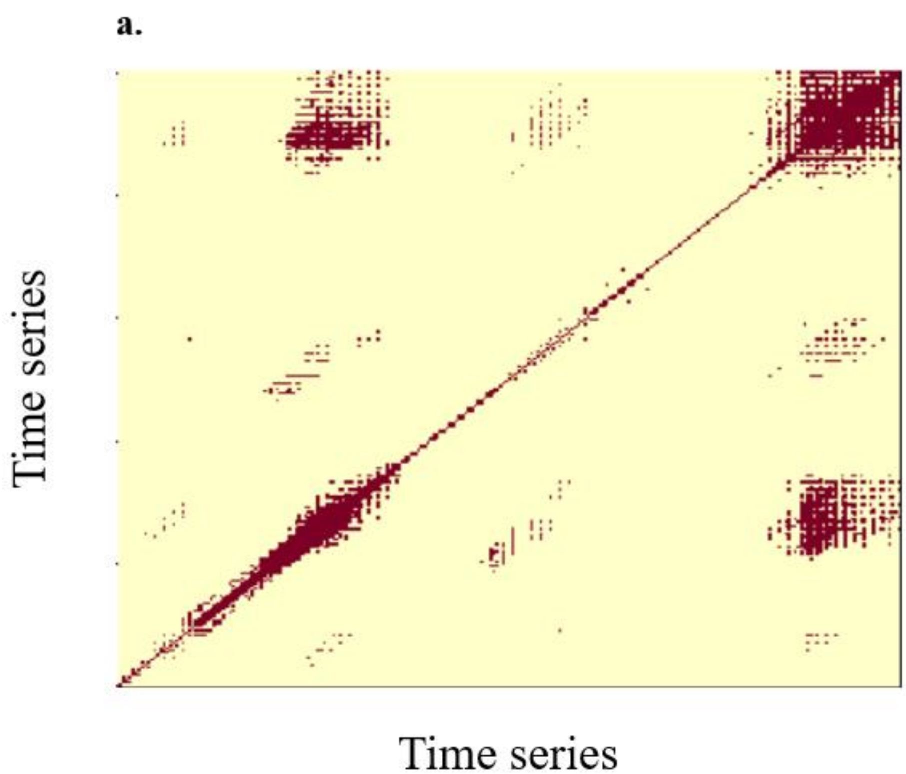
1) %DET – The measure that captures the proportion of recurrence points forming diagonal lines on the MdRP is called the determinism (DET) of the time series. Diagonal structures represent periods in the time series that follow similar paths in their time-evolution when aligned or shifted in time. The more periodic a system is (e.g.: sine waves), in terms of repeating the same paths, the more recurrences will be organized in diagonal lines.
2) Average diagonal line length – The average length of the diagonal lines represents the average time that a system repeats the same path in their time-evolution.
3) LMAX – The longest diagonal line on a recurrence plot (LMAX) represents the longest uninterrupted period that the system follows the same path, which serves as an indicator of stability of the system: for example, sensitivity to noise and external perturbations creates unstable systems and therefore a shorter longest diagonal line.
4) ENT – Entropy is a measure of complexity of the system. For a highly periodic system, the diagonal lines will be of roughly equal length throughout. As the complexity of the system increases, the diagonal lines will not have a consistent length, resulting in instability of the system.
5) %LAM – Laminarity captures the stationarity of the system by quantifying the proportion of recurrence points forming vertical lines on the RP. Vertical

structures represent length of periods in a time series in which a state does not change (repeating the same value) or changes very slowly.

The code for performing MdRQA is available in Wallot et al. (2016).

Figure 1.3

MdRP and time series for length perception kinematics data in Experiment 1. a) MdRP, b) The corresponding angular acceleration time series.



b.

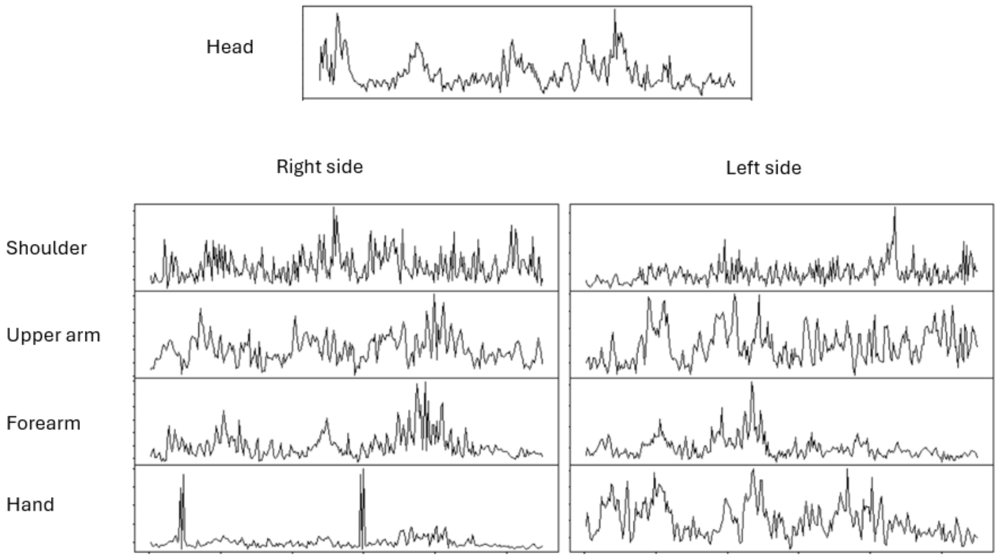
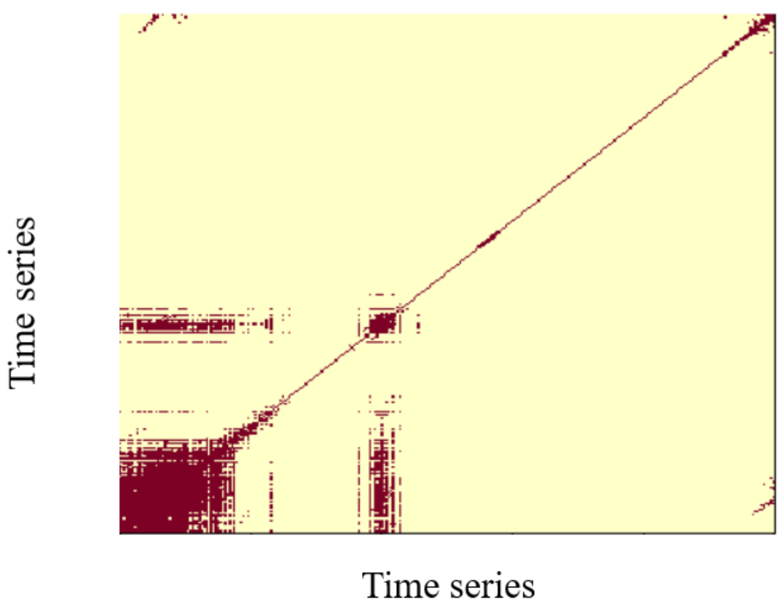


Figure 1.4

MdRP and time series for weight perception kinematics data in Experiment 1. a) MdRP, b) The corresponding angular acceleration time series.

a.



b.

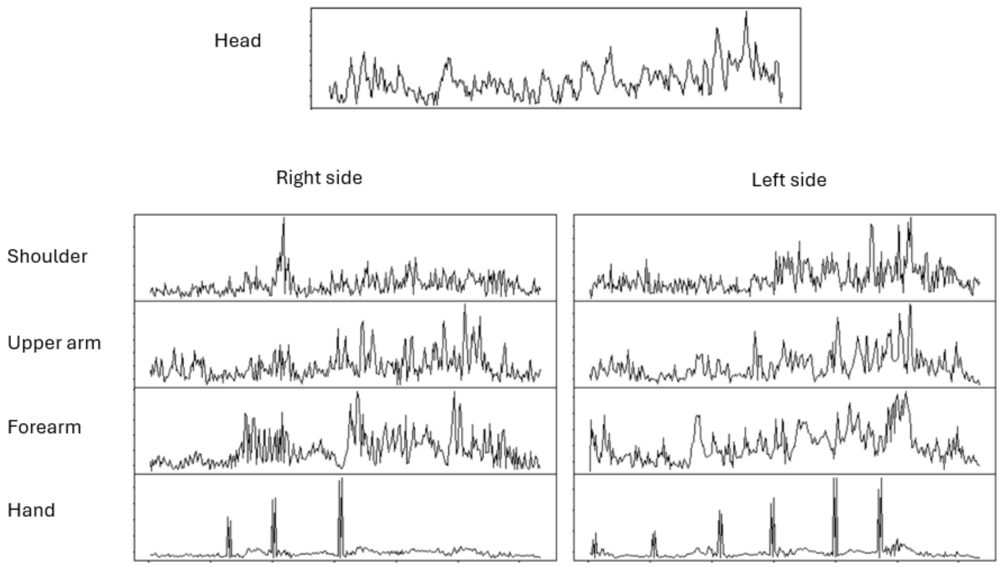
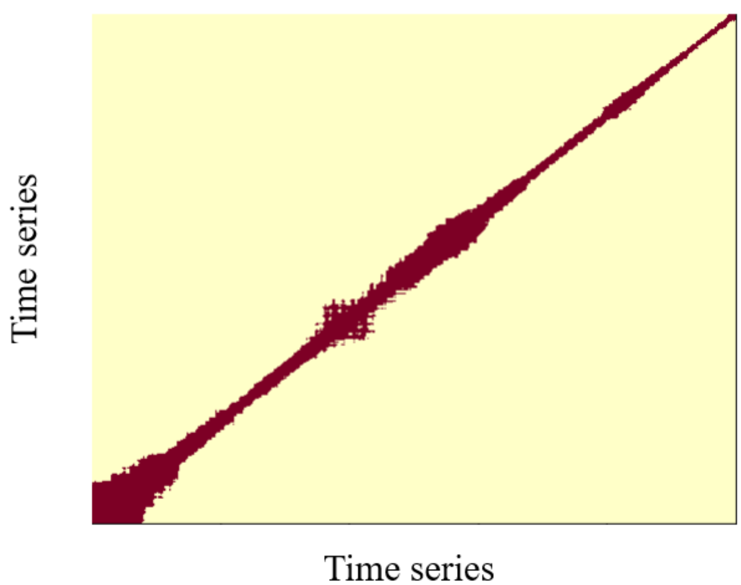


Figure 1.5

MdRP and time series for length perception EMG data in Experiment 1. a) MdRP, b) The corresponding normalized EMG time series.

a.



b.

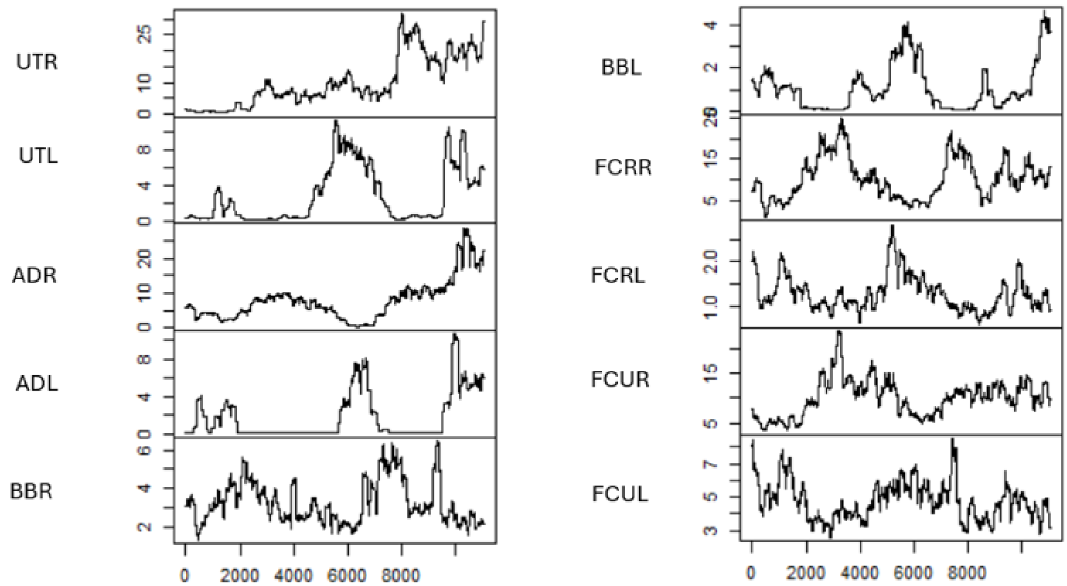
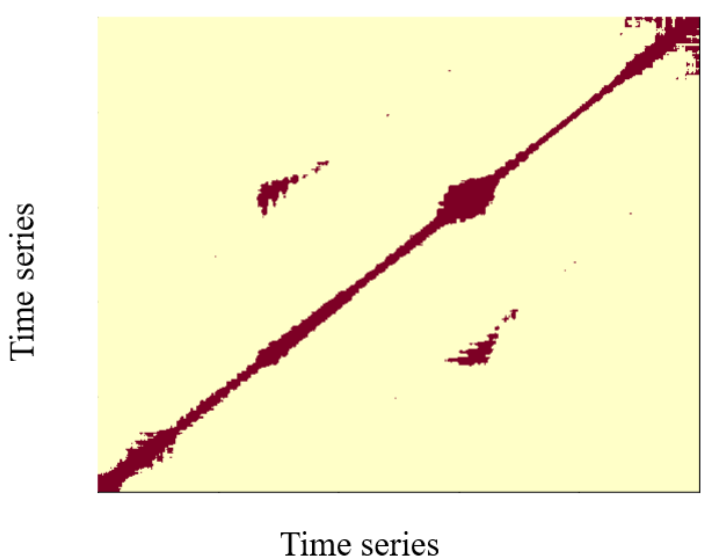


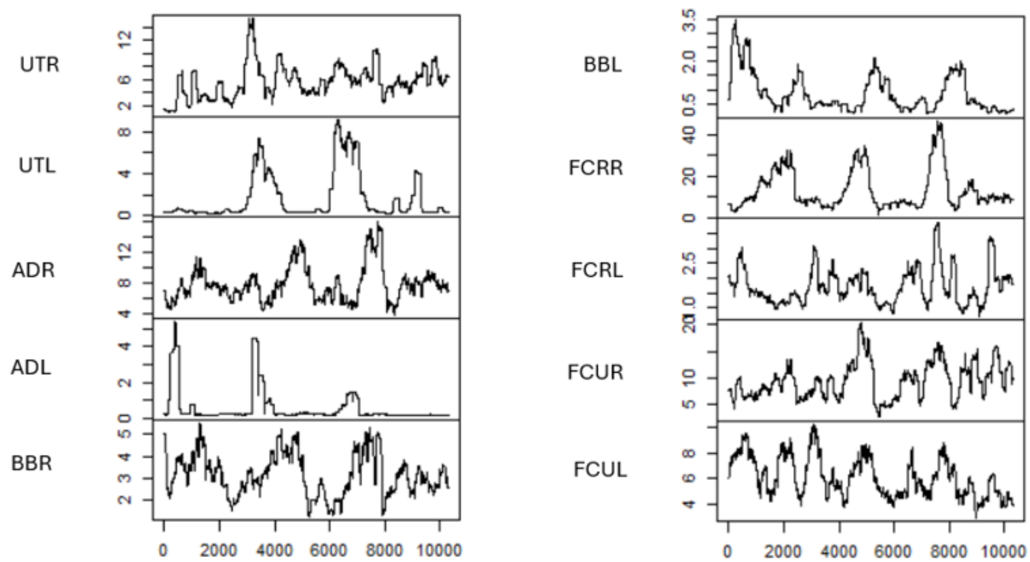
Figure 1.6

MdRP and time series for weight perception EMG data in Experiment 1. a) MdRP, b) The corresponding normalized EMG time series.

a.



b.



Statistical analysis

Since a repeated measures design was used in this experiment, variables had considerable nesting. As each participant completed 60 trials each for the length and weight perception tasks, a portion of the variance in their responses can be attributed to a common source – the fact that the same participant was responding multiple times in each condition. Level 1 (within-participant) variables represent those that change from trial to trial. Level 2 (between-participant) variables represent those that change from participant to participant.

Prior to conducting the analysis, the extent of nesting in the data was assessed by computing the intraclass correlation coefficient (ICC) from the null model for each dependent variable, using participant ID as a random effect. The average ICC was found to be 0.34 across the dependent variables. Since this is evidence of clustering by participant ID, and to properly account for variance between and within participants, multilevel modeling approach was used to analyze each dependent variable (Hofmann, 1997; Meyers, Gamst & Guarino, 2016).

Linear mixed effects models were created to test the effects of the independent variables on each dependent variable. For each analysis, an initial main effects model was run, such that the main effects were included in the analysis all at once. Results for each of these main effects are reported from the initial main effects model. Analysis of two-way interactions was done by adding each interaction term to the main effects model separately. That is, a separate model was run to obtain the results for each two-way interaction term. All models also included a random effect of participant ID. Effect sizes for each fixed effect are presented as the change in R^2 (proportion of variance explained) comparing the model that includes the effect and the same model with the effect removed. The resulting sr^2 (semi-partial r^2) is the percentage of variance uniquely accounted for by the fixed effect (Snijders & Bosker, 2011). The R code for all the statistical analysis performed in this study is shared in Appendix A.

Results

Perceived weight

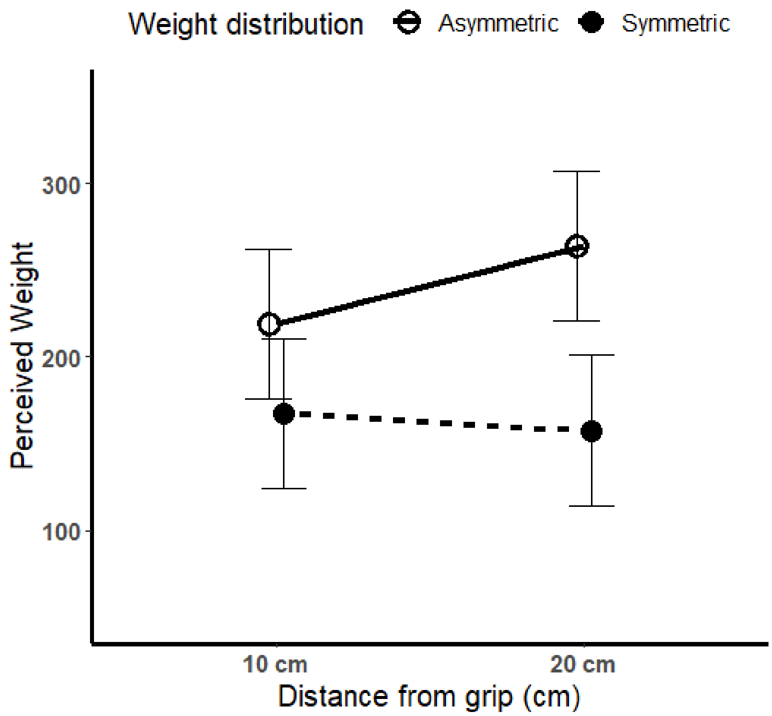
A linear mixed effects model was run to assess the effects of weight distribution (symmetrical or asymmetrical), weight position (10 cm or 20 cm away from the hands), and weight attached on the perceived weight of the rod. This model with only the main effects (*AIC* = 11568.18, *df* = 7) offered a significantly better fit to the data than did the null model (*AIC* = 11900.99, *df* = 3), $\Delta\chi^2(4) = 340.81$, $p < 0.001$. The model explained 54.4% of the variance in perceived weight (conditional $R^2 = 0.544$, marginal $R^2 = 0.194$).

The results indicate a significant effect of weight distribution on perceived weight, $F(1, 940) = 160.57$, $p < 0.001$, $sr^2 = 0.08$. The rods were perceived as significantly heavier when weights were distributed asymmetrically (*M* = 241, *SE* = 21.6) as compared to symmetrically (*M* = 163, *SE* = 21.6). There was also a significant effect of weight position on perceived weight, $F(1, 940) = 7.85$, $p = 0.005$, $sr^2 = 0.004$. The rods were perceived as significantly heavier when weights were attached 20 cm away from the hands (*M* = 211, *SE* = 21.6) as compared to 10 cm away (*M* = 193, *SE* = 21.6). There was a significant effect of the weight attached on the rod as well on perceived weight, $F(2, 940) = 120.14$, $p < 0.001$, $sr^2 = 0.12$. The rods were perceived as significantly heavier when a weight of 3 lbs. was attached to the rod (*M* = 261, *SE* = 21.8) as compared to 2 lbs. (*M* = 203, *SE* = 21.8), $t = 7.57$, $p < 0.001$, as well as 1 lb. (*M* = 142, *SE* = 21.8), $t = 15.50$, $p < 0.001$. There was also a significant difference in perceived weight when 2 lbs. were attached to the rod as compared to 1 lb., $t = 7.93$, $p < 0.001$.

The results revealed a significant interaction between weight position and weight distribution, $F(1, 939) = 19.70$, $p < 0.001$, $sr^2 = 0.009$ (Figure 1.7). When testing simple effects, when weights were attached 10 cm away from the hands, perceived weight was significantly heavier in the asymmetric distribution (*M* = 219.08, *SE* = 22.02) as compared to the symmetric distribution (*M* = 167.53, *SE* = 22.02), $t(463) = 5.42$, $p < 0.001$. Similarly, when weights were attached 20 cm away from the hands, perceived weight was significantly heavier in the asymmetric distribution (*M* = 263.91, *SE* = 22.02) as compared to the symmetric distribution (*M* = 157.61, *SE* = 22.02), *t* (463) = 10.54, $p <$ 0.001.

Figure 1.7

Interaction between weight position and weight distribution for perceived weight in Experiment 1. Error bars indicate 95% confidence interval.

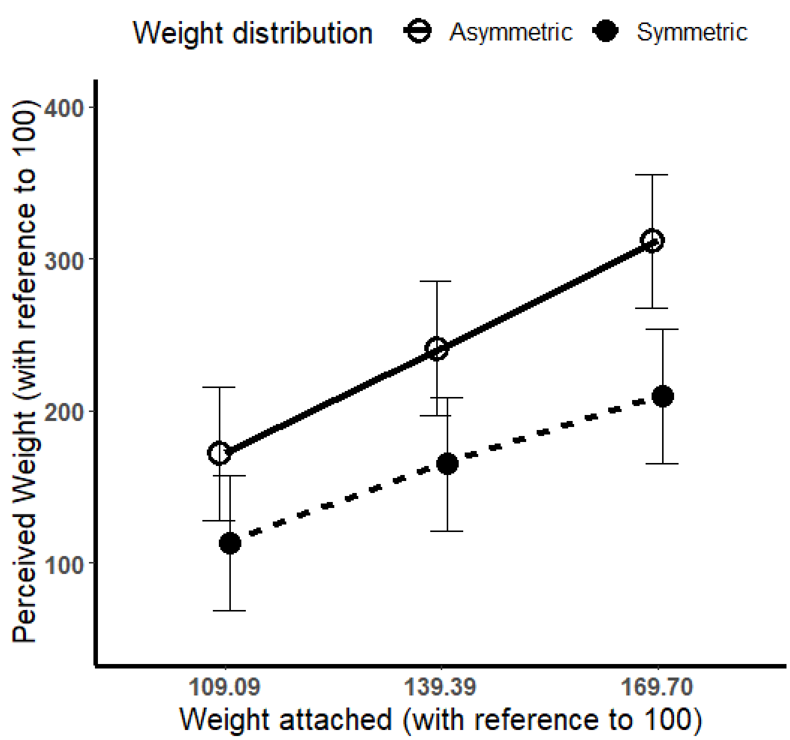


There was a significant interaction between weight distribution and weight attached as well, *F* (2, 938) = 4.08, *p* = 0.02, $sr^2 = 0.004$ (Figure 1.8). When testing simple effects, when 1 lb. weight (109.09 w.r.t the reference rod) was attached to the rod, perceived weight was significantly heavier in the asymmetric distribution (*M* = 171.85, *SE* = 22.46) as compared to the symmetric distribution (*M* = 113.07, *SE* = 22.46), *t* (303) = 6.83, $p < 0.001$. Similarly, when 2 lbs. (139.39 w.r.t the reference rod) were attached to the rod, perceived weight was significantly heavier in the asymmetric distribution (*M* =

240.98, *SE* = 22.46) as compared to the symmetric distribution (*M* = 164.93, *SE* = 22.46), t (303) = 8.61, $p < 0.001$. When 3 lbs. (169.7 w.r.t the reference rod) were attached to the rod, perceived weight was significantly heavier in the asymmetric distribution (*M* = 311.66, *SE* = 22.46) as compared to the symmetric distribution (*M* = 209.73, *SE* = 22.46), t (303) = 8.41, $p < 0.001$.

Figure 1.8

Interaction between weight attached and weight distribution for perceived weight in Experiment 1. Error bars indicate 95% confidence interval.



To test whether there was a significant relationship between perceived weight and the ratio of peak muscle activity to peak angular acceleration for each muscle pair, these pairs of ratios were added separately to the main effects model for perceived weight. For example, to assess whether there was a significant relationship between biceps brachii and the perceived weight, the ratio of peak muscle activity to peak angular acceleration for the biceps brachii on both the left and right arm were added to the main effects model for perceived weight, which already included weight distribution, weight position, and weight attached to the rod as the predictor variables.

It was found that none of these models with the ratios or their interactions added as predictor variables offered a significantly better fit to the data as compared to the main effects model.

Perceived length

A linear mixed effects model was run to assess the effects of weight distribution, weight position, and weight attached on the perceived length of the rod. This model with only the main effects (*AIC* = 7761.05, *df* = 7) did not offer a significantly better fit to the data as compared to the null model (*AIC* = 7756.99, *df* = 3), $\Delta\chi^2(4) = 3.94$, $p = 0.41$. Another linear mixed effects model was run to assess the effects of the independent variables along with all possible two-way interactions between these variables on the perceived length. This model (*AIC* = 7765, *df* = 12) also did not offer a significantly better fit to the data as compared to the null model, $\Delta\chi^2(9) = 9.99$, $p = 0.35$. The assumption of normality was met for the residuals of the mixed effects model, as confirmed in a histogram of residual distribution (Figure 1.9) and a QQ-plot of residuals (Figure 1.10). The assumption of homoscedasticity was satisfied as shown in the plot for residuals against the fitted values (Figure 1.11). Since the spread of residuals remains constant across all levels of the fitted values, the assumption of homoscedasticity is met.

Figure 1.9

Histogram of residual distribution.

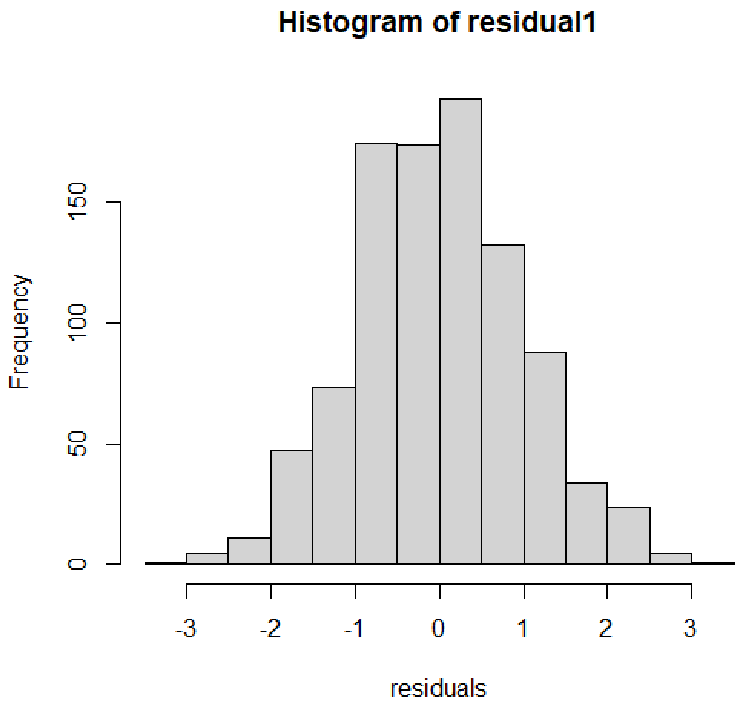


Figure 1.10

QQ-plot of residuals.

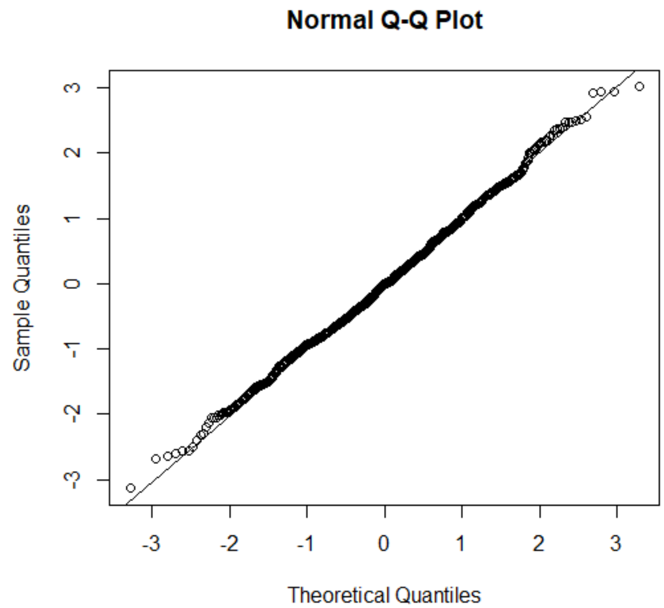
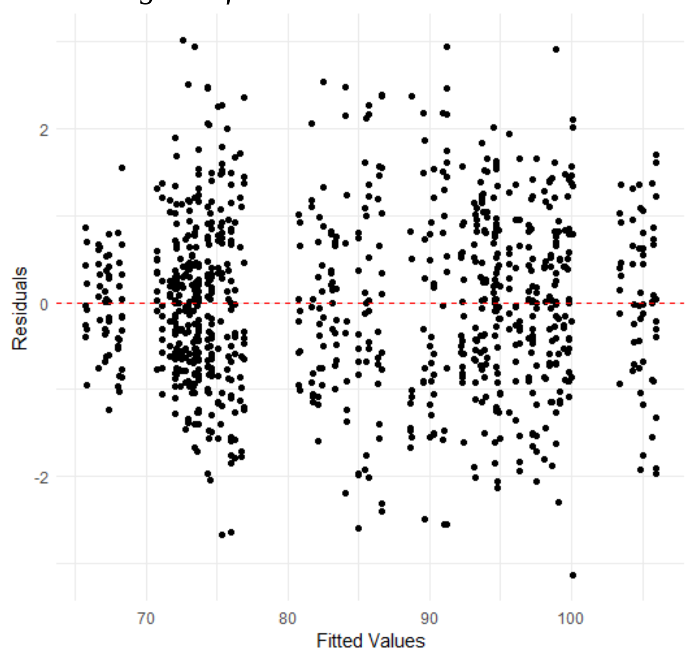


Figure 1.11

Plot of residuals against fitted values.



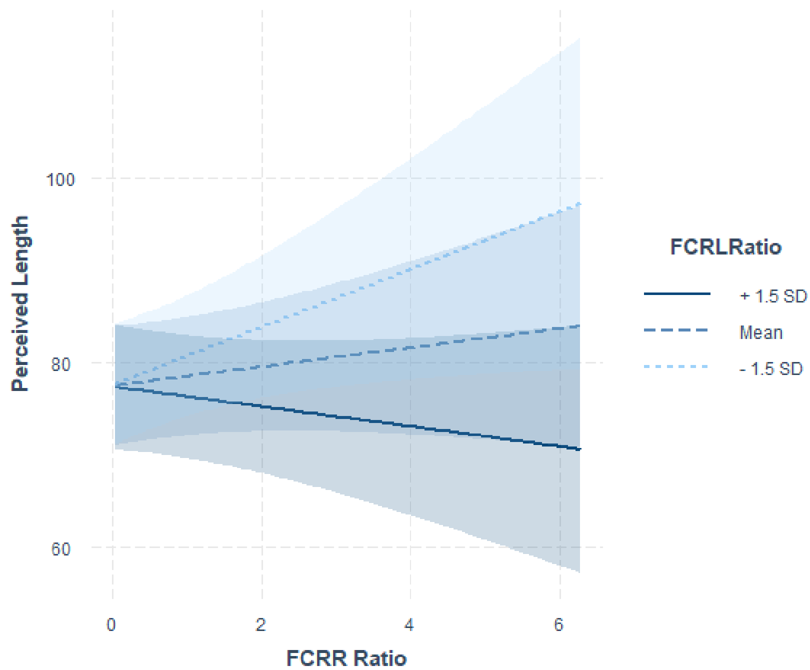
To test whether there was a significant relationship between perceived length and the ratio of peak muscle activity to peak angular acceleration for each muscle pair, these pairs of ratios were added separately to the main effects model for perceived length. The interaction between these ratios were also added to these models.

It was found that the model with ratios for the flexor carpi radialis muscles on the right and left arm, along with their interaction (*AIC* = 7645.30, *df* = 10) offered a significantly better fit to the data as compared to the main effects model (*AIC* = 7650.13, *df* = 7), $\Delta\chi^2(3) = 10.84$, *p* = 0.01.

There was a significant interaction between the ratios for flexor carpi radialis on the right hand (FCRR) and flexor carpi radialis on the left hand (FCRL), $F(1, 936) = 7.19$, *p* = 0.01, $sr^2 = 0.004$ (Figure 1.12). A test of simple slopes was conducted to check the interaction effect. It was found that when the ratio for FCRL was 1.5 SD below the mean, the simple slope for FCRR (*b* = 3.12) was positive, and statistically significant, *t* = 2.10, *p* = 0.035. However, when the ratio for FCRL was at the mean, the simple slope for FCRR (b = 1.03) was positive, but not statistically significant, *t* = 1.02, *p* = 0.32. When the ratio for FCRL was 1.5 SD above the mean, the simple slope for FCRR (*b* = -1.07) was negative, and not statistically significant, *t* = -1.02, *p* = 0.31.

Figure 1.12

Interaction between the ratio of peak muscle activity to peak angular acceleration of the hand for FCRR and FCRL in Experiment 1. Error bars indicate 95% confidence interval.



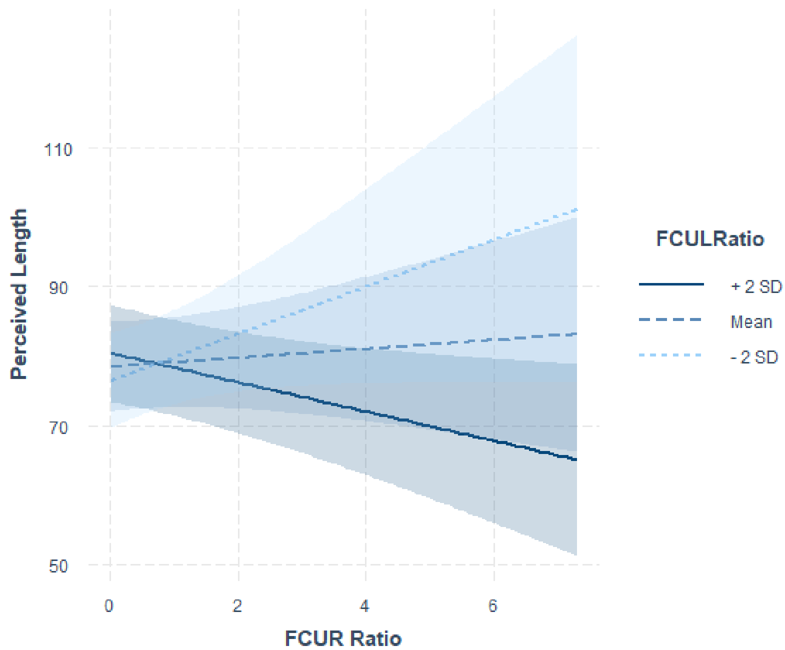
It was found that the model with ratios for the flexor carpi ulnaris muscles on the right and left arm, along with their interaction (*AIC* = 7642.36, *df* = 10) offered a significantly better fit to the data as compared to the main effects model (*AIC* = 7650.13, *df* = 7), $\Delta\chi^2(3) = 13.78$, $p = 0.003$.

There was a significant interaction between the ratios for flexor carpi ulnaris on the right hand (FCUR) and flexor carpi ulnaris on the left hand (FCUL), $F(1, 936) = 10.07$, $p = 0.002$, $sr^2 = 0.005$ (Figure 1.13). A test of simple slopes was conducted to check the interaction effect. It was found that when the ratio for FCUL was 2 SD below the mean, the simple slope for FCUR ($b = 3.38$) was positive, but not statistically significant, $t = 1.85$, $p = 0.06$. Similarly, when the ratio for FCUL was at the mean, the simple slope for FCUR (b = 0.64) was positive, but not statistically significant, $t = 0.55$, *p*

= 0.58. However, when the ratio for FCRL was 2 SD above the mean, the simple slope for FCRR (b = -2.1) was negative, and statistically significant, t = -2.27, p = 0.02.

Figure 1.13

Interaction between the ratio of peak muscle activity to peak angular acceleration of the hand for FCUR and FCUL in Experiment 1. Error bars indicate 95% confidence interval.



<u>*MdRQA variables for the EMG data*</u>

The MdRQA variables for the EMG activity for the ten muscle channels recorded were analyzed.

%DET

A linear mixed effects model was run to assess the effects of perceptual intent (weight or length), weight distribution, weight position, and weight attached on %DET.

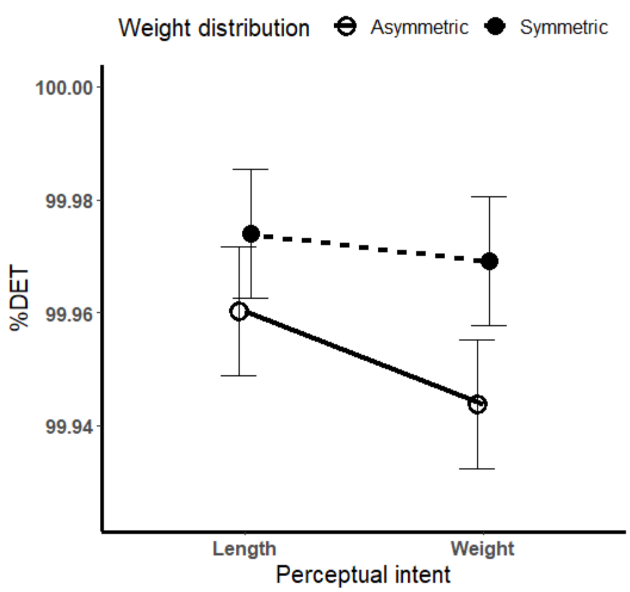
This model with only the main effects (*AIC* = -8605.67, *df* = 8) offered a significantly better fit to the data as compared to the null model (*AIC* = -8299.78, *df* = 3), $\Delta\chi^2(5)$ = 315.89, $p < 0.001$. The model explained 51.8% of the variance in %DET (conditional R^2 = 0.518, marginal R^2 = 0.104).

As expected, perceptual intent had a significant effect on %DET, F (1, 1896) = 89, $p < 0.001$, sr^2 = 0.02. %DET was significantly higher when participants intended to perceive the length of the rod (*M* = 99.97, *SE* = 0.006) as compared to the weight (*M* = 99.96, *SE* = 0.006). Weight distribution also had a significant effect on %DET, F (1, 1896) = 302, $p < 0.001$, sr^2 = 0.08. %DET was significantly higher when weights were distributed symmetrically (*M* = 99.97, *SE* = 0.006) as compared to asymmetrically (*M* = 99.95, *SE* = 0.006). There was a significant effect of weight position on %DET, F (1, 1896) = 5, p = 0.02, sr^2 = 0.001. %DET was significantly higher when weights were attached 10 cm away from the hands (*M* = 99.963, *SE* = 0.006) as compared to 20 cm away (*M* = 99.960, *SE* = 0.006). The weight attached to the rod also had a significant effect on %DET, F (2, 1896) = 8, $p < 0.001$, sr^2 = 0.004. %DET was significantly higher when 1 lb. weight was attached to the rod (*M* = 99.965, *SE* = 0.006) as compared to when 3 lbs. were attached (*M* = 99.959, *SE* = 0.006), t = 4.07, $p < 0.001$. However, there was no difference in %DET when 1 lb. weight was attached, as compared to 2 lbs. (*M* = 99.962, *SE* = 0.006), or when 2 lbs. weight were attached, as compared to 3 lbs.

There was a significant interaction between perceptual intent and weight distribution, F (1, 1895) = 27, $p < 0.001$, sr^2 = 0.007 (Figure 1.14). When testing simple effects, when participants intended to perceive the length of the rod, %DET was significantly greater in the symmetric distribution (*M* = 99.97, *SE* = 0.006) as compared to the asymmetric distribution (*M* = 99.96, *SE* = 0.006), *t* (942) = 10.35, *p* < 0.001. Similarly, when participants intended to perceive the weight of the rod, %DET was significantly greater in the symmetric distribution (*M* = 99.97, *SE* = 0.006) as compared to the asymmetric distribution (*M* = 99.94, *SE* = 0.006), *t* (941) = 15.06, *p* < 0.001.

Figure 1.14

Interaction between perceptual intent and weight distribution for %DET in Experiment 1. Error bars indicate 95% confidence interval.

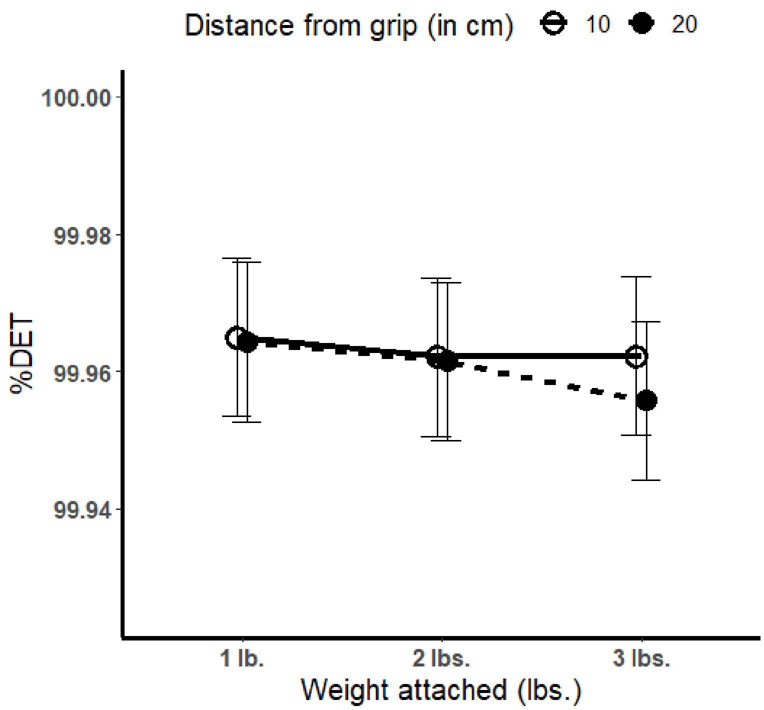


There was a significant interaction between weight position and the amount of weight attached, *F* (2, 1894) = 3, *p* = 0.049, sr^2 = 0.001 (Figure 1.15). When testing simple effects, when a weight of 3 lbs. was attached to the rod, %DET was significantly greater when the weight was attached 10 cm away from the grip (*M* = 99.962, *SE* = 0.006) as compared to 20 cm away (*M* = 99.956, *SE* = 0.006), *t* (623) = 2.71, *p* = 0.007.

However, when a weight of 2 lbs. or 1 lb. was attached to the rod, %DET was not different for the two weight positions.

Figure 1.15

Interaction between weight position and weight attached for %DET in Experiment 1. Error bars indicate 95% confidence interval.



Average diagonal line length

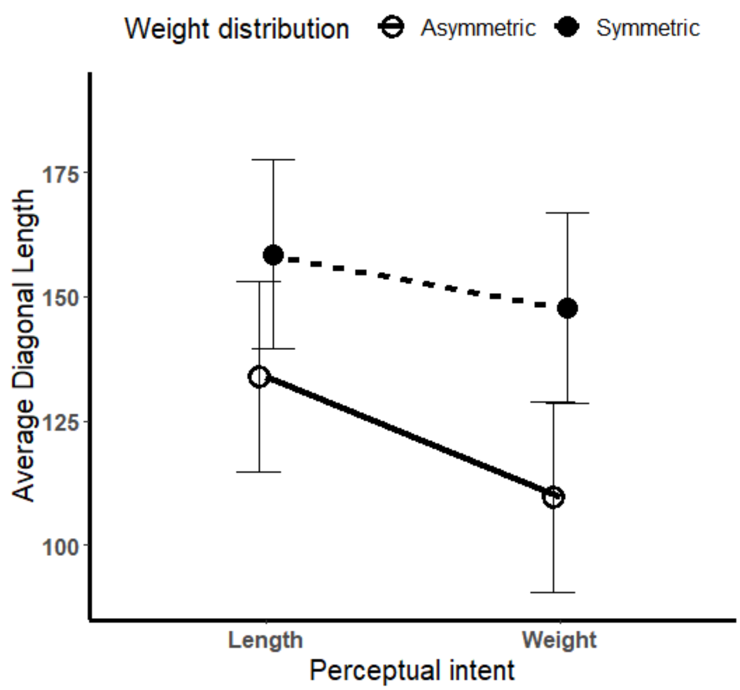
Another linear mixed effects model was run to assess the effects of the same predictor variables on average diagonal line length. This model with only the main effects (*AIC* = 20931.51, *df* = 8) offered a significantly better fit to the data than did the null model (*AIC* = 21136.72, *df* = 3), $\Delta\chi^2(5) = 215.21$, $p < 0.001$. The model explained 35.8% of the variance in average diagonal line length (conditional $R^2 = 0.358$, marginal $R^2 = 0.069$).

Perceptual intent had a significant effect on average diagonal line length, $F(1, 1896) = 46.80$, $p < 0.001$, $sr^2 = 0.02$. Average diagonal line length was significantly longer when participants intended to perceive the length of the rod ($M = 146$, $SE = 9.58$) as compared to the weight ($M = 129$, $SE = 9.58$). Weight distribution also had a significant effect on average diagonal line length, $F(1, 1896) = 148.71$, $p < 0.001$, $sr^2 = 0.05$. Average diagonal line length was significantly longer when weights were distributed symmetrically ($M = 153$, $SE = 9.58$) as compared to asymmetrically ($M = 122$, $SE = 9.58$). The weight attached to the rod had a significant effect on the average diagonal line length as well, $F(2, 1896) = 4.95$, $p = 0.007$, $sr^2 = 0.003$. Average diagonal line length was significantly longer when 1 lb. weight was attached to the rod ($M = 142$, $SE = 9.67$) as compared to when 3 lbs. were attached ($M = 132$, $SE = 9.67$), $t = 3.07$, $p = 0.006$. However, there was no difference in average diagonal line length when 1 lb. weight was attached, as compared to 2 lbs. ($M = 139$, $SE = 9.67$), or when 2 lbs. weight were attached, as compared to 3 lbs. The weight position did not have an effect on average diagonal line length.

There was a significant interaction between perceptual intent and weight distribution, $F(1, 1895) = 6.96$, $p = 0.008$, $sr^2 = 0.002$ (Figure 1.16). When testing simple effects, when participants intended to perceive the length of the rod, the average diagonal line was significantly longer in the symmetric distribution ($M = 158.54$, $SE = 9.75$) as compared to the asymmetric distribution ($M = 134.02$, $SE = 9.75$), $t(942) = 7.54$, $p < 0.001$. Similarly, when participants intended to perceive the weight of the rod, the average diagonal line was significantly longer in the symmetric distribution ($M = 147.74$, *SE* = 9.75) as compared to the asymmetric distribution (*M* = 109.71, *SE* = 9.75), *t* (941) = 10.42, $p < 0.001$.

Figure 1.16

Interaction between perceptual intent and weight distribution for Average Diagonal Length in Experiment 1. Error bars indicate 95% confidence interval.



LMAX

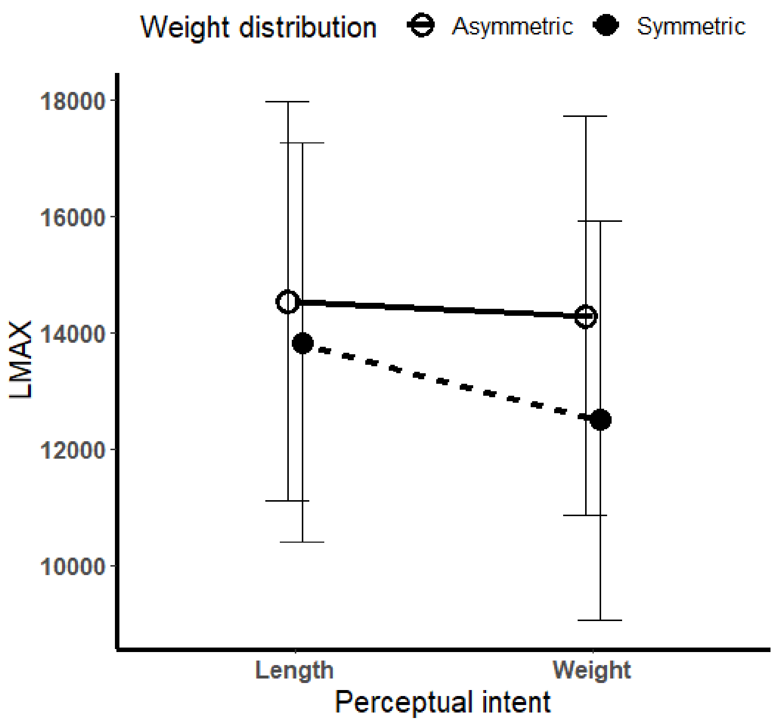
A linear mixed effects model was run to assess the effects of the same predictor variables on LMAX. This model with only the main effects (*AIC* = 38623.93, *df* = 8) offered a significantly better fit to the data as compared to the null model (*AIC* = 38718.72, *df* = 3), $\Delta\chi^2(5) = 104.79$, $p < 0.001$. The model explained 59.7% of the variance in LMAX (conditional $R^2 = 0.597$, marginal $R^2 = 0.008$).

Perceptual intent had a significant effect on LMAX, $F(1, 1896) = 9.29$, $p = 0.002$, $sr^2 = 0.002$. LMAX was significantly longer when participants intended to perceive the length of the rod (*M* = 14179, *SE* = 1740) as compared to the weight (*M* = 13382, *SE* = 1740). Weight distribution also had a significant effect on LMAX, $F(1, 1896) = 22.69$, $p < 0.001$, $sr^2 = 0.005$. LMAX was significantly longer when weights were distributed asymmetrically (*M* = 14404, *SE* = 1740) as compared to symmetrically (*M* = 13158, *SE* = 1740). Neither the weight attached to the rod, nor the weight position had a significant effect on LMAX.

There was a significant interaction between perceptual intent and weight distribution, $F(1, 1895) = 4.22$, $p = 0.04$, $sr^2 = 0.0008$ (Figure 1.17). When testing simple effects, when participants intended to perceive the length of the rod, LMAX was significantly longer in the asymmetric distribution (*M* = 14534.05, *SE* = 1750.10) as compared to symmetric distribution (*M* = 13825, *SE* = 1750.06), $t(942) = 2.26$, $p = 0.02$. Similarly, when participants intended to perceive the weight of the rod, LMAX was significantly longer in the asymmetric distribution (*M* = 14274.6, *SE* = 1750.14) as compared to symmetric distribution (*M* = 12492.03, *SE* = 1750.06), $t(941) = 5.22$, $p < 0.001$.

Figure 1.17

Interaction between perceptual intent and weight distribution for LMAX in Experiment 1. Error bars indicate 95% confidence interval.



ENT

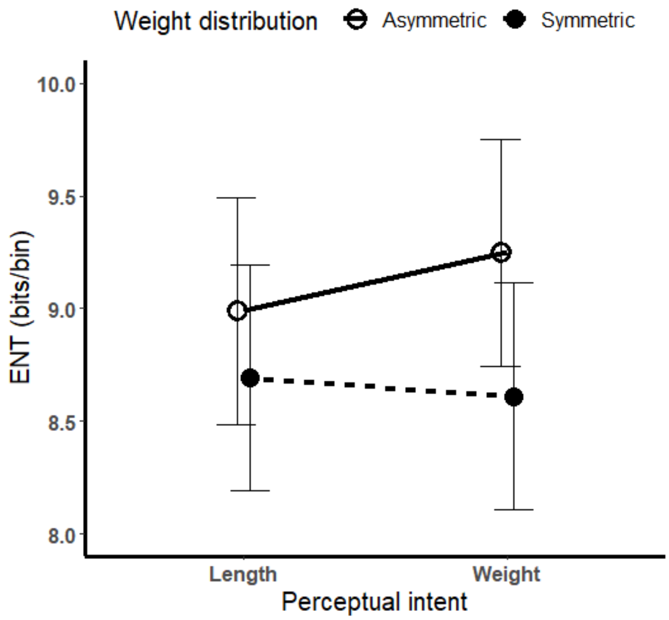
Another linear mixed effects model was run to assess the effects of the predictor variables on ENT. This model with only the main effects (*AIC* = 5780.27, *df* = 8) offered a significantly better fit to the data than did the null model (*AIC* = 5856.74, *df* = 3), $\Delta\chi^2(5) = 86.47$, $p < 0.001$. The model explained 48.9% of the variance in ENT (conditional $R^2 = 0.489$, marginal $R^2 = 0.029$).

Perceptual intent did not have an effect on ENT. However, weight distribution had a significant effect on ENT, $F(1, 1896) = 92.76$, $p < 0.001$, $sr^2 = 0.02$. ENT was significantly greater when weights were distributed asymmetrically (*M* = 9.12, *SE* = 0.26) as compared to symmetrically (*M* = 8.65, *SE* = 0.26). There was also a significant effect of weight position on ENT, $F(1, 1896) = 4.54$, $p = 0.03$, $sr^2 = 0.001$. ENTR was significantly greater when weights were attached 20 cm away from the hands (M = 8.94, SE = 0.26) as compared to 10 cm away (M = 8.83, SE = 0.26). There was a significant effect of weight attached to the rod as well on ENT, F (1, 1896) = 4.63, p = 0.01, sr^2 = 0.002. ENT was significantly greater when 3 lbs. were attached to the rod (M = 8.96, SE = 0.26) as compared to when 1 lb. was attached (M = 8.78, SE = 0.26), t = 2.95, p = 0.01. However, there was no difference in ENT when 1 lb. weight was attached, as compared to 2 lbs. (M = 8.91, SE = 0.26), or when 2 lbs. weight were attached, as compared to 3 lbs.

There was a significant interaction between perceptual intent and weight distribution, F (1, 1895) = 12.32, $p < 0.001$, sr^2 = 0.003 (Figure 1.18). When testing simple effects, when participants intended to perceive the length of the rod, ENT was significantly greater in the asymmetric distribution (M = 8.99, SE = 0.26) as compared to symmetric distribution (M = 8.69, SE = 0.26), t (942) = 5.07, $p < 0.001$. Similarly, when participants intended to perceive the weight of the rod, the ENT was significantly greater in the asymmetric distribution (M = 9.25, SE = 0.26) as compared to symmetric distribution (M = 8.61, SE = 0.26), t (941) = 9.67, $p < 0.001$.

Figure 1.18

Interaction between perceptual intent and weight distribution for ENT in Experiment 1. Error bars indicate 95% confidence interval.



%LAM

Finally, a linear mixed effects model was run to assess the effects of the predictor variables on %LAM. This model with only the main effects (*AIC* = -10508.52, *df* = 8) offered a significantly better fit to the data as compared to the null model (*AIC* = -10148.43, *df* = 3), $\Delta\chi^2(5) = 370.1$, $p < 0.001$. The model explained 49.8% of the variance in %LAM (conditional $R^2 = 0.498$, marginal $R^2 = 0.11$).

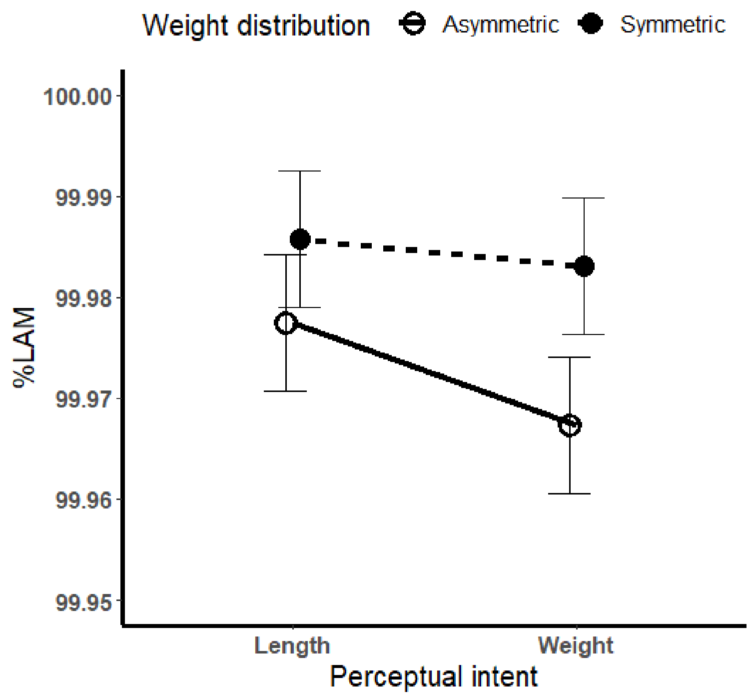
Perceptual intent had a significant effect on %LAM, $F(1, 1896) = 83$, $p < 0.001$, $sr^2 = 0.02$. %LAM was significantly higher when participants intended to perceive the length of the rod (*M* = 99.982, *SE* = 0.003) as compared to the weight (*M* = 99.975, *SE* = 0.003). Weight distribution also had a significant effect on %LAM, $F(1, 1896) = 297$, $p < 0.001$, $sr^2 = 0.08$. %LAM was significantly higher when weights were distributed symmetrically (*M* = 99.984, *SE* = 0.003) as compared to asymmetrically (*M* = 99.972, *SE* = 0.003). There was a significant effect of weight position on %LAM, $F(1, 1896) = 7$, *p*

= 0.01, sr^2 = 0.002. %LAM was significantly higher when weights were attached 10 cm away from the hands (*M* = 99.979, *SE* = 0.003) as compared to 20 cm away (*M* = 99.978, *SE* = 0.003). The weight attached to the rod also had a significant effect on %LAM, F (2, 1896) = 10, $p < 0.001$, sr^2 = 0.005. %LAM was significantly higher when 1 lb. weight was attached to the rod (*M* = 99.98, *SE* = 0.003) as compared to when 3 lbs. were attached (*M* = 99.976, *SE* = 0.003), t = 4.53, $p < 0.001$. However, there was no difference in %LAM when 1 lb. weight was attached, as compared to 2 lbs. (*M* = 99.978, *SE* = 0.003), or when 2 lbs. weight were attached, as compared to 3 lbs.

There was a significant interaction between perceptual intent and weight distribution, F (1, 1895) = 30, $p < 0.001$, sr^2 = 0.008 (Figure 1.19). When testing simple effects, when participants intended to perceive the length of the rod, %LAM was significantly greater in the symmetric distribution (*M* = 99.986, *SE* = 0.003) as compared to the asymmetric distribution (*M* = 99.977, *SE* = 0.003), t (942) = 10.07, $p < 0.001$. Similarly, when participants intended to perceive the weight of the rod, %LAM was significantly greater in the symmetric distribution (*M* = 99.983, *SE* = 0.003) as compared to the asymmetric distribution (*M* = 99.967, *SE* = 0.003), t (941) = 15.18, $p < 0.001$.

Figure 1.19

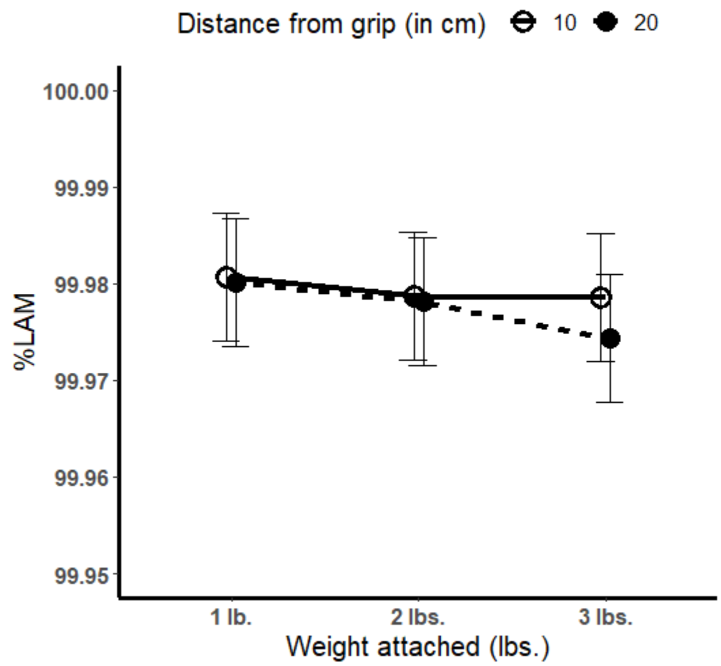
Interaction between perceptual intent and weight distribution for %LAM in Experiment 1. Error bars indicate 95% confidence interval.



There was a significant interaction between weight position and the amount of weight attached, F (2, 1894) = 3, p = 0.044, sr^2 = 0.002 (Figure 1.20). When testing simple effects, when a weight of 3 lbs. was attached to the rod, %LAM was significantly greater when the weight was attached 10 cm away from the grip (M = 99.979, SE = 0.003) as compared to 20 cm away (M = 99.974, SE = 0.003), t (623) = 2.87, p = 0.004. However, when a weight of 2 lbs. or 1 lb. was attached to the rod, %LAM was not different for the two weight positions.

Figure 1.20

Interaction between weight position and weight attached for %LAM in Experiment 1. Error bars indicate 95% confidence interval.



<u>MdRQA variables for the kinematics data</u>

The MdRQA variables for the angular acceleration of nine body segments were analyzed.

%DET

A linear mixed effects model was run to assess the effects of perceptual intent (weight or length), weight distribution, weight position, and weight attached on %DET. This model with only the main effects (*AIC* = 16182.05, *df* = 8) offered a significantly better fit to the data as compared to the null model (*AIC* = 16217.29, *df* = 3), $\Delta\chi^2(5)$ = 45.24, $p < 0.001$. The model explained 21.2% of the variance in %DET (conditional R^2 = 0.212, marginal R^2 = 0.019).

Perceptual intent had a significant effect on %DET, F (1, 1899) = 42.73, $p <$ 0.001, sr^2 = 0.02. %DET was significantly greater when participants intended to perceive the weight of the rod (*M* = 64.9, *SE* = 2.06) as compared to the length (*M* = 60.1, *SE* = 2.06). There was no significant effect of weight distribution, weight position, or weight attached on %DET. There were also no significant two-way interactions between any of the predictor variables on %DET.

Average diagonal line length

Another linear mixed effects model was run to assess the effects of the same predictor variables on average diagonal line length. This model with only the main effects (*AIC* = 9638.49, *df* = 8) offered a significantly better fit to the data than did the null model (*AIC* = 9644.88, *df* = 3), $\Delta\chi^2(5) = 16.4$, *p* = 0.006. The model explained 10.5% of the variance in average diagonal line length (conditional $R^2 = 0.105$, marginal $R^2 = 0.008$).

Perceptual intent had a significant effect on average diagonal line length, $F(1, 1899) = 11.52$, $p < 0.001$, $sr^2 = 0.005$. Average diagonal line length was significantly longer when participants intended to perceive the weight of the rod (*M* = 5.65, *SE* = 0.26) as compared to the length (*M* = 5.19, *SE* = 0.26). There was no significant effect of weight distribution, weight position, or weight attached. There were also no significant two-way interactions between any of the predictor variables on average diagonal line length.

LMAX

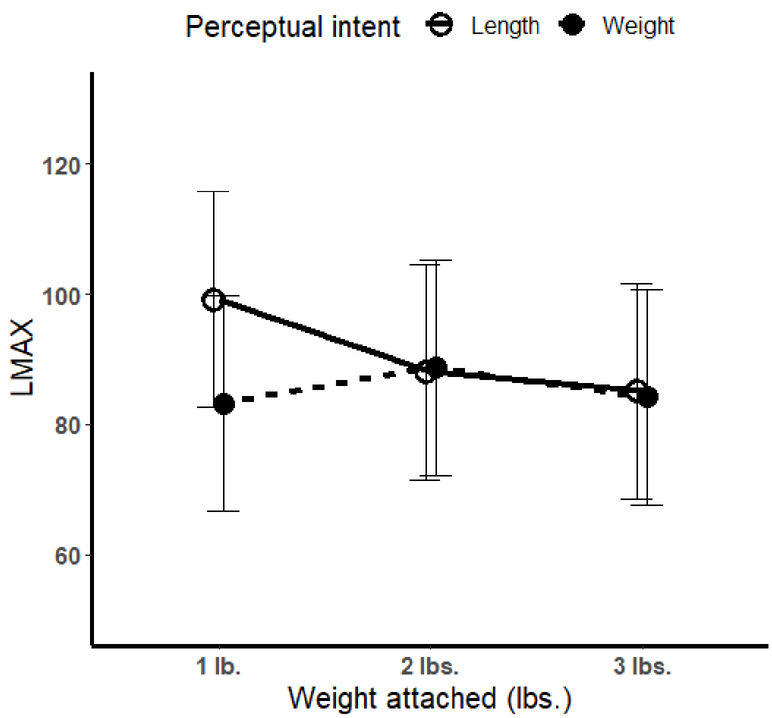
A linear mixed effects model was run to assess the effects of the same predictor variables on LMAX. This model with only the main effects (*AIC* = 20581.83, *df* = 8) offered a significantly better fit to the data as compared to the null model (*AIC* = 20588, *df* = 3), $\Delta\chi^2(5) = 16.17$, $p = 0.006$. The model explained 28.8% of the variance in LMAX (conditional $R^2 = 0.288$, marginal $R^2 = 0.006$).

Perceptual intent had a significant effect on LMAX, $F(1, 1899) = 5.45$, $p = 0.02$, $sr^2 = 0.002$. LMAX was significantly longer when participants intended to perceive the length of the rod (*M* = 90.7, *SE* = 8.12) as compared to the weight (*M* = 85.4, *SE* = 8.12). There was no significant effect of weight distribution, weight position, or weight attached on LMAX.

There was a significant interaction between perceptual intent and weight attached, $F(2, 1897) = 5.33$, $p = 0.005$, $sr^2 = 0.004$ (Figure 1.21). When testing simple effects, when 1 lb. weight was attached to the rod, LMAX was significantly longer when participants intended to perceive the length of the rod (*M* = 99.16, *SE* = 8.44) as compared to the weight (*M* = 83.19, *SE* = 8.44), $t(623) = 3.93$, $p < 0.001$. However, when a weight of 2 lbs. or 3 lbs. was attached to the rod, LMAX was not different for the two perceptual intent conditions.

Figure 1.21

Interaction between perceptual intent and weight attached for LMAX in Experiment 1. Error bars indicate 95% confidence interval.



ENT

A linear mixed effects model was run to assess the effects of the predictor variables on ENT. This model with only the main effects (*AIC* = 4899.2, *df* = 8) offered a significantly better fit to the data than did the null model (*AIC* = 4954.37, *df* = 3), $\Delta\chi^2(5) = 65.17$, $p < 0.001$. The model explained 52.4% of the variance in ENT (conditional R^2 = 0.524, marginal R^2 = 0.016).

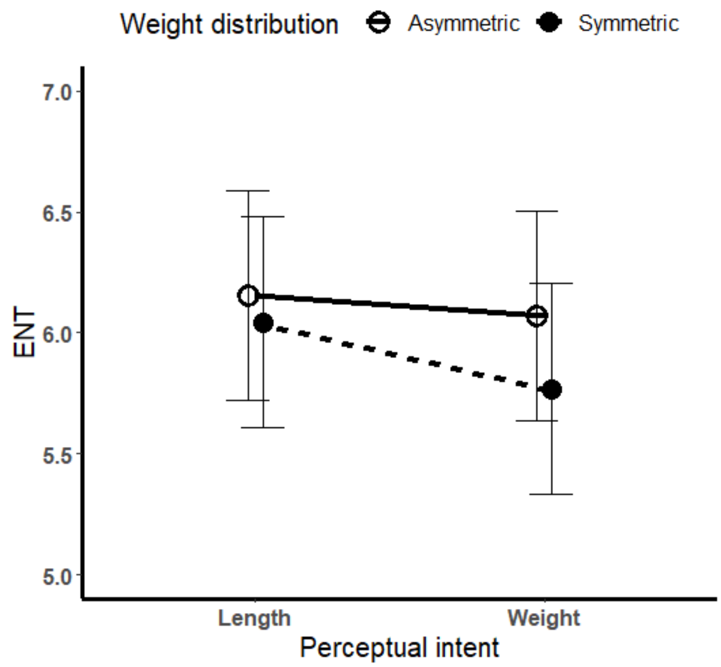
Perceptual intent had a significant effect on ENT, $F(1, 1899) = 21.52$, $p < 0.001$, $sr^2 = 0.005$. ENT was significantly greater when participants intended to perceive the length of the rod (*M* = 6.10, *SE* = 0.22) as compared to the weight (*M* = 5.92, *SE* = 0.22). Weight distribution also had a significant effect on ENT, $F(1, 1899) = 28.61$, $p < 0.001$, $sr^2 = 0.007$. ENT was significantly greater when weights were distributed asymmetrically

(*M* = 6.11, *SE* = 0.22) as compared to symmetrically (*M* = 5.91, *SE* = 0.22). There was also a significant effect of weight position on ENT, $F(1, 1899) = 4.68$, $p = 0.03$, $sr^2 = 0.001$. ENTR was significantly greater when weights were attached 20 cm away from the hands (*M* = 6.05, *SE* = 0.22) as compared to 10 cm away (*M* = 5.97, *SE* = 0.22). There was a significant effect of weight attached to the rod as well on ENT, $F(1, 1899) = 5.66$, $p = 0.004$, $sr^2 = 0.003$. ENT was significantly greater when 3 lbs. were attached to the rod (*M* = 6.09, *SE* = 0.22) as compared to when 1 lb. was attached (*M* = 5.93, *SE* = 0.22), $t = 3.35$, $p = 0.002$. However, there was no difference in ENT when 1 lb. weight was attached as compared to 2 lbs. (*M* = 6, *SE* = 0.22), or when 2 lbs. weight were attached as compared to 3 lbs.

There was a significant interaction between perceptual intent and weight distribution, $F(1, 1898) = 6.25$, $p = 0.01$, $sr^2 = 0.001$ (Figure 1.22). When testing simple effects, when participants intended to perceive the length of the rod, ENT was significantly greater in the asymmetric distribution (*M* = 6.15, *SE* = 0.22) as compared to symmetric distribution (*M* = 6.04, *SE* = 0.22), $t(943) = 2.24$, $p = 0.03$. Similarly, when participants intended to perceive the weight of the rod, the ENT was significantly greater in the asymmetric distribution (*M* = 6.07, *SE* = 0.22) as compared to symmetric distribution (*M* = 5.77, *SE* = 0.22), $t(943) = 5.81$, $p < 0.001$.

Figure 1.22

Interaction between perceptual intent and weight distribution for ENT in Experiment 1. Error bars indicate 95% confidence interval.



%LAM

A linear mixed effects model was run to assess the effects of the predictor variables on %LAM. This model with only the main effects (*AIC* = 14901.27, *df* = 8) offered a significantly better fit to the data as compared to the null model (*AIC* = 14918.09, *df* = 3), $\Delta\chi^2(5) = 26.82$, $p < 0.001$. The model explained 21.3% of the variance in %LAM (conditional $R^2 = 0.213$, marginal $R^2 = 0.011$).

Perceptual intent had a significant effect on %LAM, $F(1, 1899) = 24.42$, $p < 0.001$, $sr^2 = 0.01$. %LAM was significantly greater when participants intended to perceive the weight of the rod (*M* = 75, *SE* = 1.51) as compared to the length (*M* = 72.4, *SE* =

1.51). There was no significant effect of weight distribution, weight position, or weight attached on %LAM. There were also no significant two-way interactions between any of the predictor variables on %LAM.

Discussion

The focus of this experiment was to investigate participants' perception of heaviness and length when wielding rods with varying characteristics bimanually. Although previous work on dynamic touch includes studies on heaviness and length perception, as per our knowledge, none of these studies have explored this in the context of bimanual wielding of objects, taking symmetric or asymmetric distribution of weights into consideration. MdRQA, a multivariate, nonlinear time series analysis technique was used to study the dynamics of exploratory movements and muscle activity, as participants wielded the rods.

Statistical analysis of perceived heaviness revealed that when weights were asymmetrically biased to the participants' right side as they wielded the rod, they perceived it to be heavier as compared to a symmetrical distribution of weights, supporting a part of hypothesis 1. This was expected because in the case of asymmetrical weight distribution, participants had to exert an additional torque to balance the downward torque brought about by the weight on one side, while this was balanced out by the weight on the other side of the rod, in the case of symmetric distribution. This result is also consistent with previous studies which suggest that the maximum acceptable weight of lifting was lower in the case of asymmetrical lifting loads (Mital & Fard, 1986).

Previous studies on dynamic touch underline that inertia tensor is the invariant information in the haptic array that specifies heaviness and length of hand-held objects (Amazeen & Turvey, 1996; Blau & Wagman, 2022; Carello, Santana & Burton, 1996; Pagano & Turvey, 1992; Pagano et al., 1993; Shockley et al., 2004; Solomon & Turvey, 1988). In the current study, participants perceived the rods to be heavier when weights were attached farther from the grip position as opposed to a closer position, thus supporting a part of hypothesis 2. Since moving the weights farther increases the moment of inertia about the geometric center of the rod, it was expected that perceived heaviness would increase in this case. This result aligns with previous research, again indicating the similarity between bimanual and unimanual heaviness perception.

As expected, the results indicate that perceived heaviness increased consistently as the magnitude of weight attached to the rod increased. This supported a part of hypothesis 3. A closer look at the interaction between weight distribution and weight attached, on perceived heaviness, indicates that as the attached weight increased, participants were more accurate in judging the weight of the rod in the case of symmetrical distribution, as compared to asymmetrical distribution.

Surprisingly, there was no effect of weight distribution, weight position, or the magnitude of weight attached, on the perceived length of the rod. Therefore, parts of hypotheses 1, 2 and 3 were not supported. In general, participants seemed to be very accurate in the length perception task, where the actual length of the rods used was 91.4 cm, and the mean perceived length was 84.63 cm. Future studies should explore length perception in bimanual wielding, with rods of different lengths and weights attached, to understand the role played by inertia tensor in such tasks. Perhaps the inertia tensor plays a less significant role in bimanual length perception. If this is the case, future research should identify other invariant information that could specify the length of bimanually wielded objects.

The analysis of the relationship between perceived length and the ratio of peak muscle activity to peak angular acceleration of the corresponding body segment revealed significant interactions between the flexor carpi radialis muscles on the right and left forearm, as well as between the flexor carpi ulnaris muscles on the right and left forearm. This indicates the role played by these forearm muscles in length perception tasks. However, this is in contrast with the findings by Mangalam et al. (2019), where the role played by flexor carpi radialis and ulnaris were confirmed for heaviness perception, but not for length perception. It should be noted that the current study design did not control the amount of time, or the way participants wielded the rods, and hence it is difficult to infer the role played by individual muscles on perceived heaviness and length. On average, participants wielded the rods for 6.92 seconds when they were trying to perceive the length, while they wielded them for 6.54 seconds when trying to perceive the heaviness. This is one key reason why the dynamics of muscle activity and movements were explored in the current study, which could tell us about the synergy and coordination between multiple muscles, as well as between the different segments of the upper body involved in heaviness and length perception.

The dynamics of EMG activity of the ten muscles on the upper body revealed high periodicity in the activity of these muscles. This indicates that tasks like length and heaviness perception demand several muscles on the upper body to work together in concinnity (Turvey, 2007). It was found that the activity of the ten muscles considered for the current study was more deterministic and stable during the length perception task as compared to heaviness perception. For MdRQA, a higher value of %DET indicates more periodicity, while a greater value of average diagonal line length and LMAX indicate more stability. A higher %LAM indicates that the activity of these muscles was not changing rapidly during length perception as compared to heaviness perception (Weber & Marwan, 2014). Taken together, these results support hypothesis 4. This also provides evidence supporting the co-specificity hypothesis, since the dynamics of muscle activity are different when people have an intention to perceive the length of the rod as compared to its heaviness (Arzamarski et al., 2010; Riley et al., 2002).

Symmetric distribution of weights resulted in greater determinism and stationarity in the activity of the muscles. Although the average diagonal length indicates that on average there were longer periods of recurring patterns of muscle activity in symmetric distribution, the LMAX indicates that the longest period of recurring pattern of muscle activity occurred in the asymmetric distribution. Asymmetric distribution also resulted in greater entropy. Together, these results indicate that movements were more complex and chaotic in asymmetric distribution as compared to symmetric distribution of weights. This supports hypothesis 5.

The coordinated activity between the muscles considered in this study was more deterministic and stationary when the weights were attached closer to the grip position. Since the moment of inertia about the grip position was smaller in this case, it might have caused a smaller perturbation to the system as compared to when the weights were attached farther from the grip, which resulted in a larger moment of inertia and therefore a larger perturbation. In conjunction with this, it was also found that the entropy was greater when the weights were attached farther, resulting in more chaotic movements in this case. These results support hypothesis 6.

As expected, the muscle activity was more deterministic and stationary when the magnitude of weight attached was 1 lb. as compared to 3 lbs. However, interaction effects between the magnitude and position of weight attached indicates that this difference was more pronounced when 3 lbs. were attached farther, 20 cm away from the grip position. A lower entropy when 1 lb. weight was attached as compared to 3 lbs. indicates that the movements were more stable when 1 lb. weight was attached. These results support hypothesis 7.

The dynamics of the angular acceleration of nine segments of the upper body analyzed in this study revealed that participants' exploratory movements were more deterministic and stable when they intended to perceive the weight of the rod as compared to its length. This result supports hypothesis 8. This also provides further evidence to support the co-specificity hypothesis which ties together an organism's intention, exploratory behavior and the information that specifies an affordance (Arzamarski et al., 2010; Riley et al., 2002). In this case, participants' exploratory movements were different depending on whether they intended to perceive the length or weight of the rod. Additionally, since the moment of inertia plays a major role in perceiving the heaviness of hand-held objects (Amazeen & Turvey, 1996; Shockley et al., 2004), while both the moment and product of inertia play a role in length perception (Carello et al., 1996), these affordances are specified by different sources of invariant information.

CHAPTER THREE

EXPERIMENT 2

Experiment 2 was conducted to test whether the use of ASEs could change how participants perceive the weight of hand-held objects, as they extend their hands over their shoulder to heft and wield the objects. It was expected that wearing an ASE would alter the muscle activity and torque needed to heft and wield objects. However, participants might still be able to perceive the relative differences in weights as in experiment 1. The design of experiment 2 was similar to experiment 1. The only difference was that the perceptual intent manipulation was dropped. Participants only performed the weight perception task for this experiment.

Hypotheses

H1: When the weight is distributed asymmetrically, perceived heaviness will increase as compared to when weight is distributed symmetrically.

H2: When weights are placed farther from the grip position, perceived heaviness will increase as compared to when weights are placed closer to the grip position.

H3: When the magnitude of weight attached to the rods increases, perceived heaviness will increase.

H4: The dynamics of muscle activity will be different when participants wield rods with weights distributed symmetrically as compared to asymmetrically.

H5: The dynamics of muscle activity will be different when participants wield rods with weights attached closer to the gripped position, as compared to weights attached farther away.

H6: The dynamics of muscle activity will become less periodic and less stable when the magnitude of the weight attached to the rod increases.

H7: Perceived heaviness will show a weak relationship with the ratio of EMG activity to lifting acceleration for the biceps brachii, flexor carpi radialis, and flexor carpi ulnaris.

H8: The dynamics of the movements of the segments of the upper body will be the same when participants wield different rods.

Method

Participants

Sixteen Clemson University students participated in the study for partial course credit, or for a $30 gift card, after providing informed consent (8 females, age $M = 19.88$, $SD = 2.25$). Participants did not have any self-reported musculoskeletal injuries within 12 months prior to participation. The study was performed with approval of the Institutional Review Board of Clemson University.

Apparatus and material

In addition to the equipment and material used in experiment 1, Ekso Bionics EVO (Figure 2.1), a passive arm-support exoskeleton was used in experiment 2. It consists of a waist strap and arm straps, the size of which were selected to fit each participant. Interchangeable spring cartridges could be used to change the exoskeleton torque/support strength, and an internal linkage system converted spring compression into shoulder moment. The torque setting could be adjusted to one of three levels – low, medium, or high, but was set to medium throughout the study.

Figure 2.1

Ekso Bionics EVO upper-arm exoskeleton (Retrieved from https://eksobionics.com/ekso-evo/)

<u>*Procedure, experimental design and data preparation*</u>

The procedure followed in experiment 1 was followed for experiment 2 as well. After attaching the EMG electrodes and sensors, and the motion tracking sensors, participants donned the exoskeleton with assistance from the experimenter, the experimenter turned it on, and then the participant familiarized themselves with it. This was followed by the weight perception task done in experiment 1. Prior to the task, the headpiece of a stadiometer was adjusted to 10 degrees above the participant's shoulder height. Participants stretched their forearms, with their palms facing up, and their hands in line with the headpiece of the stadiometer (Figure 2.2). Participants were allowed to heft and wield the rod only above their shoulder level. Participants judged the weight of different rods given to them with reference to a reference rod which weighed 100, as in experiment 1.

Figure 2.2

Participant wielding the rod above shoulder level.

<u>Results</u>

<u>Perceived weight</u>

A linear mixed effects model was run to assess the effects of weight distribution, weight position, and weight attached on the perceived weight of the rod. This model with only the main effects (*AIC* = 10996.91, *df* = 7) offered a significantly better fit to the data than did the null model (*AIC* = 11229.07, *df* = 3), $\Delta\chi^2(4) = 240.16$, $p < 0.001$. The model explained 45.3% of the variance in perceived weight (conditional $R^2 = 0.453$, marginal $R^2 = 0.155$).

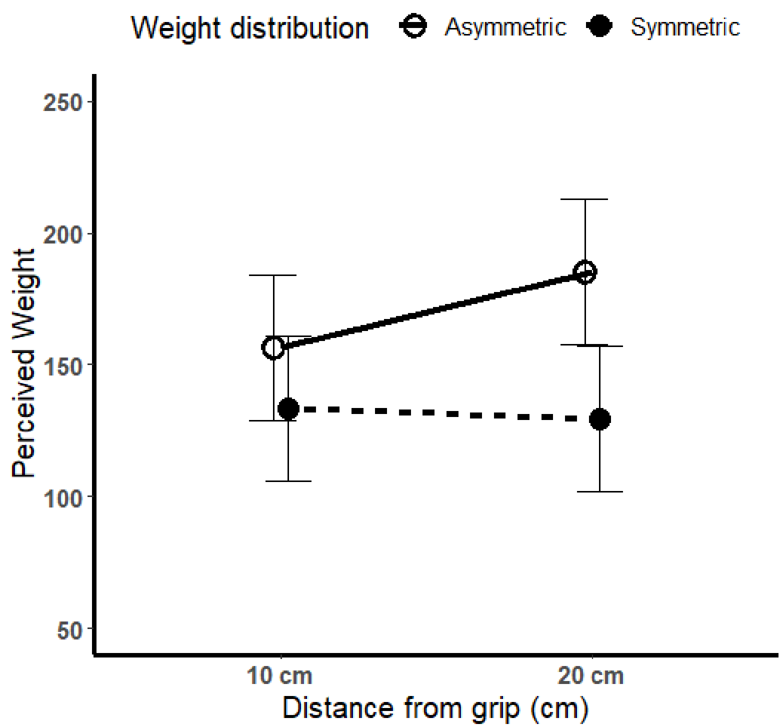
The results indicate a significant effect of weight distribution on perceived weight, $F(1, 940) = 72.24$, $p < 0.001$, $sr^2 = 0.04$. The rods were perceived as significantly heavier when weights were distributed asymmetrically (*M* = 171, *SE* = 13.7) as compared to symmetrically (*M* = 131, *SE* = 13.7). There was also a significant effect of weight position on perceived weight, $F(1, 940) = 7.13$, $p = 0.008$, $sr^2 = 0.004$. The rods were perceived as significantly heavier when weights were attached 20 cm away from the hands (*M* = 157, *SE* = 13.7) as compared to 10 cm away (*M* = 145, *SE* = 13.7). There was a significant effect of the weight attached on the rod as well on perceived weight, $F(2, 940) = 96.47$, $p < 0.001$, $sr^2 = 0.11$. The rods were perceived as significantly heavier when a weight of 3 lbs. was attached to the rod (*M* = 190, *SE* = 13.8) as compared to 2 lbs. (*M* = 153, *SE* = 13.8), $t = 6.5$, $p < 0.001$, as well as 1 lb. (*M* = 111, *SE* = 13.8), $t = 13.88$, $p < 0.001$. There was also a significant difference in perceived weight when 2 lbs. were attached to the rod as compared to 1 lb., $t = 7.38$, $p < 0.001$.

The results revealed a significant interaction between weight position and weight distribution, $F(1, 939) = 12.52$, $p < 0.001$, $sr^2 = 0.007$ (Figure 2.3). When testing simple effects, when weights were attached 10 cm away from the hands, perceived weight was significantly heavier in the asymmetric distribution (*M* = 156.54, *SE* = 14.03) as compared to the symmetric distribution (*M* = 133.43, *SE* = 14.03), $t(463) = 3.99$, $p <$

0.001. Similarly, when weights were attached 20 cm away from the hands, perceived weight was significantly heavier in the asymmetric distribution (M = 185.24, SE = 14.03) as compared to the symmetric distribution (M = 129.51, SE = 14.03), t (463) = 6.69, $p <$ 0.001.

Figure 2.3

Interaction between weight position and weight distribution for perceived weight in Experiment 2. Error bars indicate 95% confidence interval.

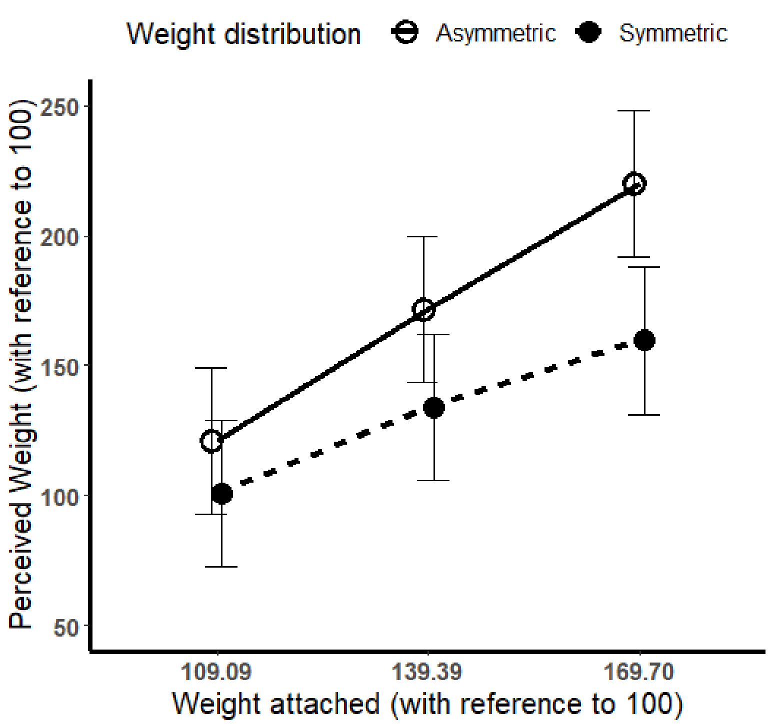


There was a significant interaction between weight distribution and weight attached as well, F (2, 938) = 6.32, p = 0.002, sr^2 = 0.007 (Figure 2.4). When testing simple effects, when 1 lb. weight (109.09 w.r.t the reference rod) was attached to the rod, perceived weight was significantly heavier in the asymmetric distribution (M = 121.02, SE = 14.41) as compared to the symmetric distribution (M = 100.83, SE = 14.41), t (303)

= 6.10, $p < 0.001$. Similarly, when 2 lbs. (139.39 w.r.t the reference rod) were attached to the rod, perceived weight was significantly heavier in the asymmetric distribution (M = 171.75, SE = 14.41) as compared to the symmetric distribution (M = 133.94, SE = 14.41), t (303) = 6.37, $p < 0.001$. When 3 lbs. (169.7 w.r.t the reference rod) were attached to the rod, perceived weight was significantly heavier in the asymmetric distribution (M = 219.91, SE = 14.41) as compared to the symmetric distribution (M = 159.64, SE = 14.41), t (303) = 5.76, $p < 0.001$.

Figure 2.4

Interaction between weight attached and weight distribution for perceived weight in Experiment 2. Error bars indicate 95% confidence interval.



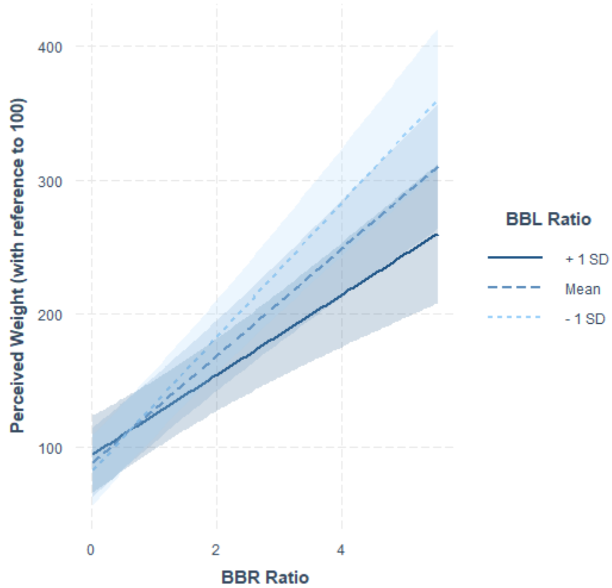
To test whether there was a significant relationship between perceived weight and the ratio of peak muscle activity to peak angular acceleration for each muscle pair, these pairs of ratios were added separately to the main effects model for perceived weight. The interaction between these ratios were also added to these models.

It was found that the model with ratios for the biceps brachii muscles on the right and left arm, along with their interaction (*AIC* = 10908.36, *df* = 10) offered a significantly better fit to the data as compared to the main effects model (*AIC* = 10996.91, *df* = 7), $\Delta\chi^2(3) = 94.55$, $p < 0.001$.

There was a significant interaction between the ratios for the biceps brachii on the right hand (BBR) and the biceps brachii on the left hand (BBL), $F\,(1, 937) = 11.52$, $p < 0.001$, $sr^2 = 0.01$ (Figure 2.5). A test of simple slopes was conducted to check the interaction effect. It was found that when the ratio for BBL was 1 SD below the mean, the simple slope for BBR ($b = 50.48$) was positive and statistically significant, $t = 9.61$, $p < 0.001$. Similarly, when the ratio for BBL was at the mean, the simple slope for BBR (b = 40.26) was positive and statistically significant, $t = 9.18$, $p < 0.001$. When the ratio for BBL was 1 SD above the mean, the simple slope for BBR ($b = 30.04$) was again positive and statistically significant, $t = 5.58$, $p < 0.001$.

Figure 2.5

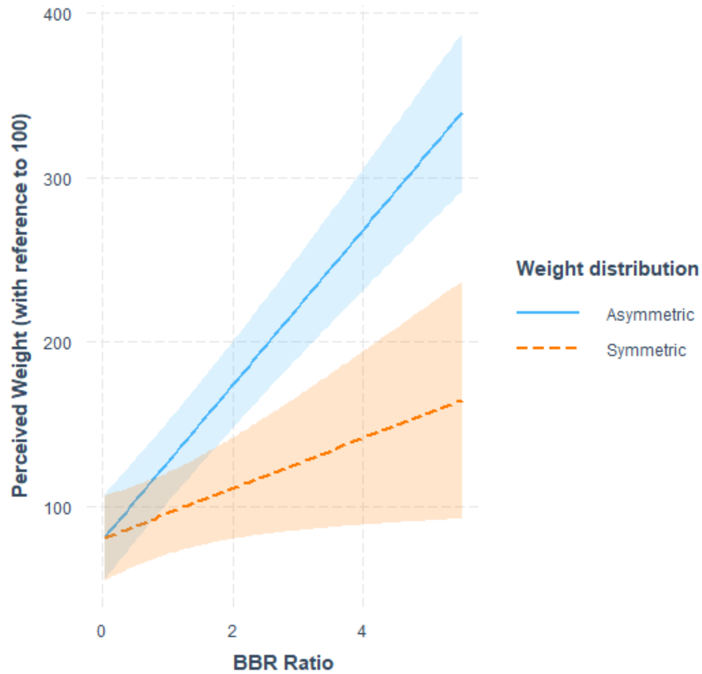
Interaction between the ratio of peak muscle activity to peak angular acceleration of the hand for BBR and BBL. Error bars indicate 95% confidence interval.



There was a significant interaction between the ratio for BBR and the type of weight distribution, $F(1, 937) = 20.58$, $p < 0.001$, $sr^2 = 0.003$ (Figure 2.6). Weight distribution altered the relation between the ratio of peak muscle activity to the peak angular acceleration of the right forearm for BBR, and perceived weight. A test of simple slopes revealed that for both asymmetric and symmetric weight distribution, the simple slope for the ratio for BBR was positive. Symmetric distribution had a shallower slope ($b = 15.23$, $t = 2.14$, $p = 0.03$) as compared to asymmetric distribution ($b = 47.01$, $t = 10.26$, $p < 0.001$).

Figure 2.6

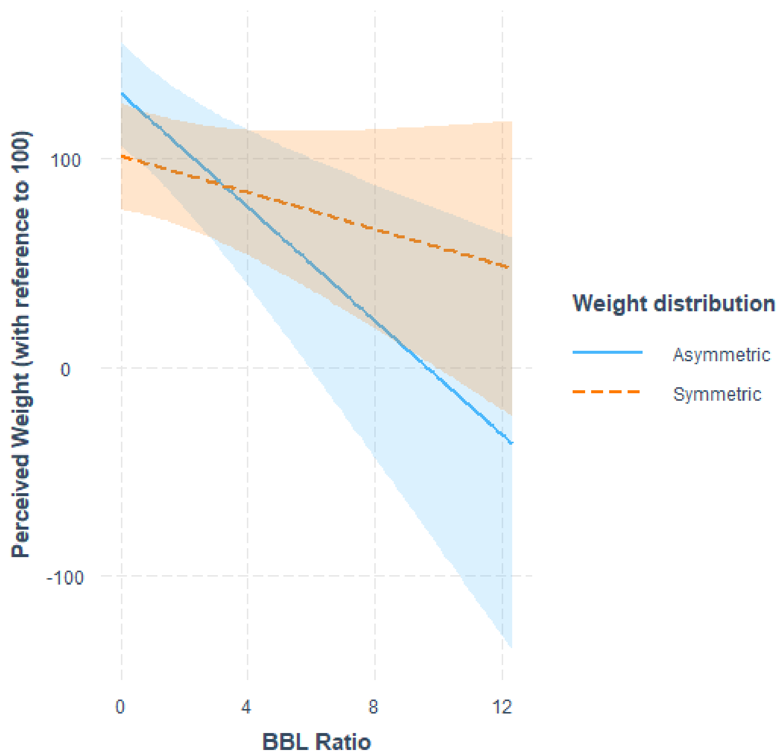
Interaction between weight distribution and the ratio of peak muscle activity to peak angular acceleration of the hand for BBR. Error bars indicate 95% confidence interval.



There was a significant interaction between the ratio for BBL and the type of weight distribution, F (1, 937) = 4.08, p = 0.04, sr^2 = 0.002 (Figure 2.7). Weight distribution altered the relation between the ratio of peak muscle activity to the peak angular acceleration of the left forearm for BBL, and perceived weight. A test of simple slopes revealed that for both asymmetric and symmetric weight distribution, the simple slope for the ratio for BBL was negative. Symmetric distribution had a shallower, non-significant slope (b = -4.36, t = -1.45, p = 0.15) as compared to asymmetric distribution (b = -13.58, t = -3.28, p = 0.001).

Figure 2.7

Interaction between weight distribution and the ratio of peak muscle activity to peak angular acceleration of the hand for BBL. Error bars indicate 95% confidence interval.



<u>*MdRQA variables for the EMG data*</u>

The MdRQA variables for the EMG activity for the ten muscle channels recorded were analyzed.

%DET

A linear mixed effects model was run to assess the effects of weight distribution, weight position, and weight attached on %DET. This model with only the main effects (*AIC* = -4595.73, *df* = 7) offered a significantly better fit to the data as compared to the null model (*AIC* = -4536.24, *df* = 3), $\Delta\chi^2(4) = 67.49$, $p < 0.001$. The model explained 46.4% of the variance in %DET (conditional $R^2 = 0.464$, marginal $R^2 = 0.039$).

Weight distribution had a significant effect on %DET, $F(1, 940) = 63$, $p < 0.001$, $sr^2 = 0.034$. %DET was significantly higher when weights were distributed symmetrically (*M* = 99.96, *SE* = 0.005) as compared to asymmetrically (*M* = 99.95, *SE* = 0.006). There was no significant effect of weight position, or weight attached on %DET. There were also no significant two-way interactions between any of the predictor variables on %DET.

Average diagonal line length

Another linear mixed effects model was run to assess the effects of the same predictor variables on average diagonal line length. This model with only the main effects (*AIC* = 9932.28, *df* = 7) offered a significantly better fit to the data than did the null model (*AIC* = 9972.47, *df* = 3), $\Delta\chi^2(4) = 48.19$, $p < 0.001$. The model explained 36.4% of the variance in average diagonal line length (conditional $R^2 = 0.364$, marginal $R^2 = 0.033$).

Weight distribution had a significant effect on average diagonal line length, $F(1, 940) = 38.68$, $p < 0.001$, $sr^2 = 0.03$. Average diagonal line length was significantly longer when weights were distributed symmetrically (*M* = 106.4, *SE* = 7.69) as compared to asymmetrically (*M* = 89.8, *SE* = 7.69). The weight attached to the rod had a significant effect on the average diagonal line length as well, $F(2, 940) = 4.82$, $p = 0.008$, $sr^2 = 0.006$. Average diagonal line length was significantly longer when 3 lbs. of weight were attached to the rod (*M* = 103.9, *SE* = 7.8) as compared to when 1 lb. was attached (*M* = 94.9, *SE* = 7.8), $t = 2.77$, $p = 0.02$, and also when 2 lbs. were attached (*M* = 95.4, *SE* = 7.8), $t = 2.6$, $p = 0.03$. However, there was no difference in average diagonal line length when 1 lb. weight was attached, as compared to 2 lbs.

There was no significant effect of weight position on average diagonal line length. There were also no significant two-way interactions between any of the predictor variables on average diagonal line length.

LMAX

A linear mixed effects model was run to assess the effects of the same predictor variables on LMAX. This model with only the main effects (*AIC* = 18747.72, *df* = 7) did not offer a significantly better fit to the data as compared to the null model (*AIC* = 18801.5, *df* = 3), $\Delta\chi^2(4) = 61.78$, $p < 0.001$. The model explained 66.9% of the variance in LMAX (conditional $R^2 = 0.669$, marginal $R^2 = 0.003$).

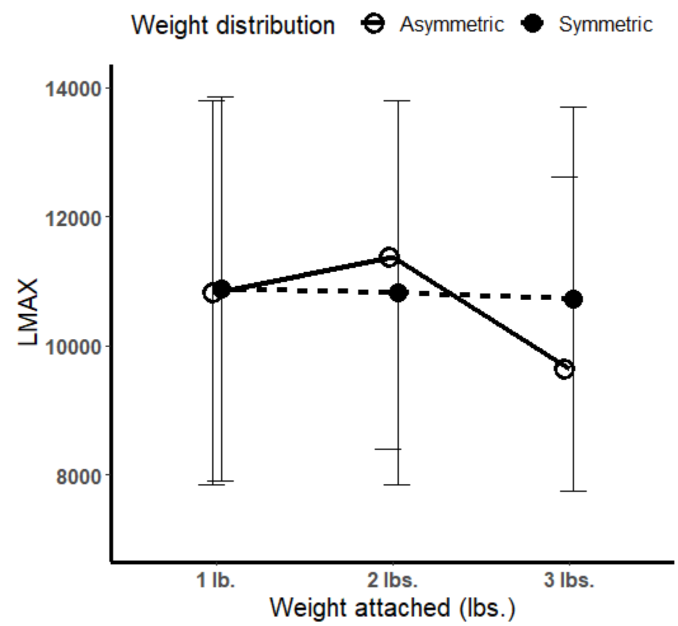
The weight attached to the rod had a significant effect on LMAX, $F(2, 940) = 4.18$, $p = 0.02$, $sr^2 = 0.002$. LMAX was significantly shorter when 3 lbs. were attached to the rod (*M* = 10178, *SE* = 1497) as compared to when 2 lbs. were attached (*M* = 11099, *SE* = 1497), $t = 2.79$, $p = 0.01$. However, there was no difference in LMAX when 3 lbs. were attached to the rod as compared to 1 lb. (*M* = 10854, *SE* = 1497), or when 1 lb. was compared to 2 lbs. There was no significant effect of weight position or weight distribution on LMAX.

There was a significant interaction between weight distribution and weight attached, $F(2, 938) = 3.2$, $p = 0.04$, $sr^2 = 0.002$ (Figure 2.8). When testing simple effects, when 3 lbs. were attached to the rod, LMAX was significantly longer in the symmetric distribution (*M* = 10720.19, *SE* = 1514.94) as compared to the asymmetric distribution (*M* = 9635.27, *SE* = 1514.94), $t(303) = 2.62$, $p = 0.01$. However, when 1 lb. or 2 lbs.

were attached to the rod, there was no significant difference in LMAX between the symmetric and asymmetric weight distributions.

Figure 2.8

Interaction between weight attached and weight distribution for LMAX in Experiment 2. Error bars indicate 95% confidence interval.



ENT

A linear mixed effects model was run to assess the effects of the predictor variables on ENT. This model with only the main effects (*AIC* = 2769.34, *df* = 7) offered a significantly better fit to the data than did the null model (*AIC* = 2776.98, *df* = 3), $\Delta\chi^2(4) = 15.65$, *p* = 0.004. The model explained 62.3% of the variance in ENT (conditional $R^2 = 0.623$, marginal $R^2 = 0.006$).

The weight attached to the rod had a significant effect on ENT, $F(2, 940) = 6.05$, *p* = 0.003, $sr^2 = 0.004$. ENT was significantly lesser when 3 lbs. were attached to the rod (*M* = 8.44, *SE* = 0.32) as compared to when 2 lbs. were attached (*M* = 8.68, *SE* = 0.32), *t*

= -3.13, $p = 0.005$, and also compared to when 1 lb. was attached to the rod ($M = 8.66$, $SE = 0.32$), $t = -2.88$, $p = 0.01$. However, ENT was not different when 1 lb. was attached to the rod, as compared to when 2 lbs. were attached.

There was no significant effect of weight position or weight distribution on ENT. There were also no significant two-way interactions between any of the predictor variables on ENT.

%LAM

A linear mixed effects model was run to assess the effects of the predictor variables on %LAM. This model with only the main effects ($AIC = -5456.65$, $df = 7$) offered a significantly better fit to the data as compared to the null model ($AIC = -5402.59$, $df = 3$), $\Delta\chi^2(4) = 62.06$, $p < 0.001$. The model explained 48.1% of the variance in %LAM (conditional $R^2 = 0.481$, marginal $R^2 = 0.035$).

Weight distribution had a significant effect on %LAM, $F(1, 940) = 57$, $p < 0.001$, $sr^2 = 0.03$. %LAM was significantly higher when weights were distributed symmetrically ($M = 99.976$, $SE = 0.003$) as compared to asymmetrically ($M = 99.970$, $SE = 0.003$). There was no significant effect of weight position, or weight attached on %LAM. There were also no significant two-way interactions between any of the predictor variables on %LAM.

MdRQA variables for the kinematics data

The MdRQA variables for the angular acceleration of nine body segments were analyzed.

%DET

A linear mixed effects model was run to assess the effects of weight distribution, weight position, and weight attached on %DET. This model with only the main effects (*AIC* = 7898.94, *df* = 7) did not offer a significantly better fit to the data as compared to the null model (*AIC* = 7897.68, *df* = 3), $\Delta\chi^2(4) = 6.73$, $p = 0.15$. Another linear mixed effects model was run to assess the effects of the predictor variables along with a two-way interaction between weight distribution and weight attached. This model (*AIC* = 7896.07, *df* = 9) also did not offer a significantly better fit to the data as compared to the null model, $\Delta\chi^2(9) = 14.71$, $p = 0.09$.

Average diagonal line length

A linear mixed effects model was run to assess the effects of weight distribution, weight position, and weight attached on average diagonal line length. This model with only the main effects (*AIC* = 4192.04, *df* = 7) did not offer a significantly better fit to the data as compared to the null model (*AIC* = 4192.57, *df* = 3), $\Delta\chi^2(4) = 8.53$, $p = 0.07$. Another linear mixed effects model was run to assess the effects of the independent variables along with all possible two-way interactions between these variables on the perceived length. This model (*AIC* = 4195.59, *df* = 12) also did not offer a significantly better fit to the data as compared to the null model, $\Delta\chi^2(9) = 14.99$, $p = 0.09$.

LMAX

A linear mixed effects model was run to assess the effects of the same predictor variables on LMAX. This model with only the main effects (*AIC* = 9532.05, *df* = 7) did not offer a significantly better fit to the data as compared to the null model (*AIC* =

9542.05, $df = 3$), $\Delta\chi^2(4) = 18$, $p = 0.001$. The model explained 38.8% of the variance in LMAX (conditional $R^2 = 0.388$, marginal $R^2 = 0.012$).

The weight attached to the rod had a significant effect on LMAX, $F(2, 940) = 7.19$, $p < 0.001$, $sr^2 = 0.009$. LMAX was significantly longer when 1 lb. was attached to the rod ($M = 68.7$, $SE = 6.83$) as compared to when 3 lbs. ($M = 58.8$, $SE = 6.83$), $t = 3.75$, $p < 0.001$, and compared to when 2 lbs. were attached to the rod ($M = 62.5$, $SE = 6.83$), $t = 2.38$, $p = 0.047$. However, LMAX was not different when 2 lbs. were attached to the rod as compared to 3 lbs. There was no significant effect of weight position or weight distribution on LMAX. There were also no significant two-way interactions between any of the predictor variables on LMAX.

ENT

A linear mixed effects model was run to assess the effects of the same predictor variables on ENT. This model with only the main effects ($AIC = 2359.28$, $df = 7$) did not offer a significantly better fit to the data as compared to the null model ($AIC = 2363.93$, $df = 3$), $\Delta\chi^2(4) = 12.65$, $p = 0.01$. The model explained 63% of the variance in ENT (conditional $R^2 = 0.63$, marginal $R^2 = 0.005$).

The weight attached to the rod had a significant effect on ENT, $F(2, 940) = 4.01$, $p = 0.02$, $sr^2 = 0.003$. ENT was significantly lesser when 3 lbs. were attached to the rod ($M = 5.5$, $SE = 0.26$) as compared to 2 lbs. ($M = 5.66$, $SE = 0.26$), $t = 2.65$, $p = 0.02$. However, ENT was not different when 3 lbs. were attached to the rod as compared to 1 lb. ($M = 5.63$, $SE = 0.26$), or when 1 lb. was attached to the rod compared to 2 lbs. There was no significant effect of weight position or weight distribution on ENT. There were also no significant two-way interactions between any of the predictor variables on ENT.

%LAM

A linear mixed effects model was run to assess the effects of the same predictor variables on %LAM. This model with only the main effects (*AIC* = 7111.52, *df* = 7) did not offer a significantly better fit to the data as compared to the null model (*AIC* = 7114.67, *df* = 3), $\Delta\chi^2(4) = 11.15$, *p* = 0.025. The model explained 26% of the variance in %LAM (conditional $R^2 = 0.26$, marginal $R^2 = 0.009$).

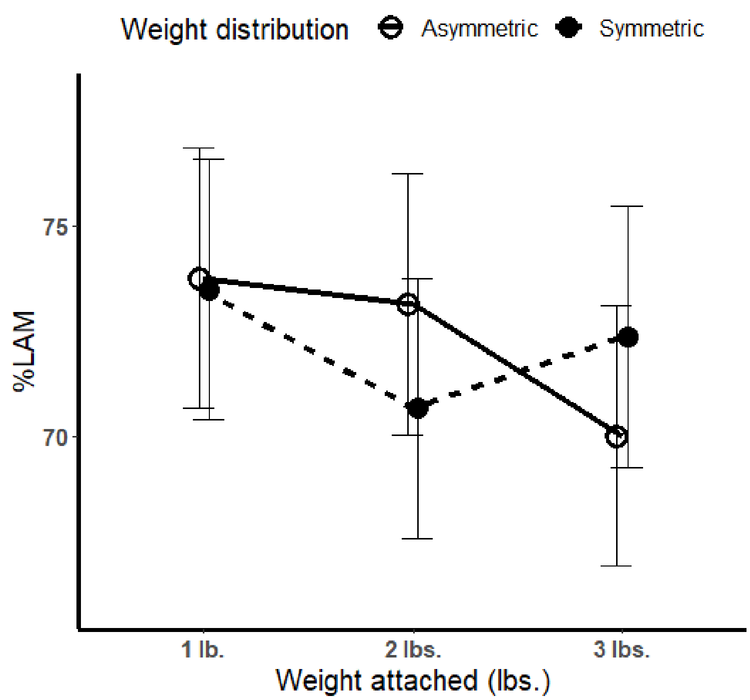
The weight attached to the rod had a significant effect on %LAM, $F(2, 940) = 5.55$, *p* = 0.004, $sr^2 = 0.008$. %LAM was significantly lesser when 3 lbs. were attached to the rod (*M* = 71.2, *SE* = 1.49) as compared to 1 lb. (*M* = 73.6, *SE* = 1.49), *t* = 3.24, *p* = 0.004. However, %LAM was not different when 3 lbs. were attached to the rod as compared to 2 lbs. (*M* = 71.9, *SE* = 1.49), or when 2 lbs. were attached to the rod as compared to 1 lb. There was no significant effect of weight position or weight distribution on %LAM.

There was a significant interaction between weight distribution and weight attached, $F(2, 938) = 5.18$, *p* = 0.006, $sr^2 = 0.008$ (Figure 2.9). When testing simple effects, when 3 lbs. were attached to the rod, %LAM was significantly greater in the symmetric distribution (*M* = 72.34, *SE* = 1.58) as compared to the asymmetric distribution (*M* = 70, *SE* = 1.58), *t* (303) = 2.18, *p* = 0.03. When 2 lbs. were attached to the rod, %LAM was significantly greater in the asymmetric distribution (*M* = 73.13, *SE* = 1.58) as compared to the symmetric distribution (*M* = 70.65, *SE* = 1.58), *t* (303) = 2.34, *p*

= 0.02. However, when 1 lb. was attached to the rod, there was no significant difference in %LAM between the symmetric and asymmetric weight distributions.

Figure 2.9

Interaction between weight attached and weight distribution for %LAM in Experiment 2. Error bars indicate 95% confidence interval.



<u>Discussion</u>

The focus of experiment 2 was to investigate participants' perception of heaviness when wielding rods with varying characteristics above the shoulder level, as they wear an ASE. Experiment 2 was conducted as an extension of experiment 1 which explored bimanual wielding of objects, taking symmetric or asymmetric distribution of weights into consideration. As per our knowledge, this is the first study that investigates dynamic touch while wearing an ASE. Similar to experiment 1, the differences in perceived heaviness based on the weights attached on the wielded rods were studied, while MdRQA was used to study the dynamics of exploratory movements and muscle activity, as participants wielded the rods.

Similar to experiment 1, statistical analysis of perceived heaviness revealed that when weights were asymmetrically biased to the participants' right side, they perceived it to be heavier as compared to a symmetrical distribution of weights, supporting hypothesis 1. In the case of asymmetrical weight distribution, even with an ASE on, participants had to exert an additional torque to balance the downward torque brought about by the weight on one side, while this was balanced out by the weight on the other side of the rod, in the case of symmetric distribution. This result is consistent with the results of experiment 1 and also previous studies which suggest that the maximum acceptable weight of lifting was lower in the case of asymmetrical lifting loads (Mital & Fard, 1986).

Previous studies on dynamic touch show that inertia tensor is the invariant information in the haptic array that specifies heaviness and length of hand-held objects (Amazeen & Turvey, 1996; Blau & Wagman, 2022; Carello, Santana & Burton, 1996; Pagano & Turvey, 1992; Pagano et al., 1993; Shockley et al., 2004; Solomon & Turvey, 1988). In the current study, similar to experiment 1, participants perceived the rods to be heavier when weights were attached farther from the grip position as opposed to a closer position, thus supporting hypothesis 2. This indicates that even with an ASE on, people still perceive weights based on the moment of inertia.

As expected, the results indicate that perceived heaviness increased consistently as the magnitude of weight attached to the rod increased, supporting hypothesis 3. A closer look at the interaction between weight distribution and weight attached on perceived heaviness indicates that as the attached weight increased, participants were not accurate in judging the weight of the rod, neither in the case of symmetrical distribution nor the asymmetrical distribution of weights. Overall, the results indicate that the ASE might have affected the accuracy of heaviness judgments, although people still perceive the relation between different weights in the same way they do without an ASE.

The analysis of the relationship between perceived weight and the ratio of peak muscle activity to peak angular acceleration of the corresponding body segment revealed significant interactions between the biceps brachii muscles on the right and left arm. This indicates the role played by these muscles in heaviness perception. This aligns well with the findings by Mangalam et al. (2019), where the role played by the biceps brachii muscle was confirmed for heaviness perception. There was also a significant interaction between this ratio for the right bicep muscle and the weight distribution. For the asymmetric distribution of weights, there was a steeper increase in perceived heaviness with an increase in the ratio, as compared to the symmetric distribution. In the case of the left bicep brachii, however, as the ratio of peak muscle activity to peak angular acceleration increased, the perceived heaviness seemed to be reducing. Since most of the participants were right-handed, it might be the case that they were exerting much more force on the rod using their right hand as compared to the left.

It should be noted that in the current study design, participants wielded the rods above their shoulder level, with their elbow straight. This should generally activate the shoulder muscles, the upper trapezius and anterior deltoid. However, there was no direct relation between the ratio of peak velocity to peak angular acceleration for these muscles. For this reason, similar to experiment 1, it was expected that the dynamics of muscle activity and movements could play a role, which could tell us about the synergy and coordination between multiple muscles, as well as between the different segments of the upper body involved in heaviness perception.

Similar to experiment 1, the dynamics of EMG activity of the ten muscles on the upper body indicate that it was highly deterministic. Symmetric distribution of weights resulted in greater determinism and stationarity in the activity of the muscles. On average there were longer periods of recurring patterns of muscle activity in symmetric distribution as compared to asymmetric distribution of weights. These results indicate that muscle activity was more periodic and stable in symmetric distribution as compared to asymmetric distribution of weights. This supports hypothesis 4.

There was no clear effect of the magnitude of weight attached to the rods, or the position of weight attached, on the periodicity or stationarity of exploratory muscular activity pattern. However, when 3 lbs. were attached to the rods, the movements were less complex, as compared to when 2 lbs. or 1 lb. weights were attached. This effect was more pronounced in the asymmetric distribution of weights as compared to symmetric distribution. These results do not support hypotheses 5 and 6. This could indicate that the torque support from the ASE was helping participants more when they were wielding rods with 3 lbs. attached, as compared to 2 lbs. or 1 lb. Perhaps a larger downward torque from the rod was met with a large resistive upward torque from the ASE in the case of 3 lb. rods, stabilizing the muscular activity in this case.

The dynamics of the angular acceleration of nine segments of the upper body analyzed in this study revealed that participants' exploratory movements were more stationary and stable when they were wielding rods with 1 lb. attached, as compared to 3 lbs. This result does not support hypothesis 8. Perhaps the lighter weights made participants' movements more stationary and stable. That is, there was no change, or slower change in the pattern of angular acceleration as participants held 1 lb. rods as compared to 3 lbs. Given these results it is possible that participants perceived the difference in heaviness between different weight magnitudes, based on such differences in movement and muscle activity for wielding different rods. Perhaps they might have quickly calibrated to the torque support and movement patterns that resulted from the use of ASEs, which could have helped them perceive the relative differences in heaviness between the different rods. Future studies should explore whether and how participants calibrate to the effects of wearing an ASE and perceive affordances like heaviness and length of hand-held objects.

CHAPTER FOUR

General Discussion

In experiment 1, participants wielded weight attached rods to perceive either their length or heaviness, providing insights into the coordination of exploratory movements, dynamics of muscular activity, and perception. While previous research on dynamic touch has examined aspects of heaviness and length perception, to our knowledge, none of these studies have investigated these phenomena within the context of bimanual object wielding, particularly considering symmetric or asymmetric distribution of weights. It was found that participants perceived the rods to be heavier if the weights attached were distributed asymmetrically, if they were attached farther from the grip position, and if the magnitude of weights increased. However, none of these manipulations affected the perceived length.

Building upon these findings, experiment 2 introduced the use of an ASE, having participants to wield the rods above shoulder level to perceive their heaviness. This extension of the experimental design was aimed at investigating whether the integration of assistive technology, like an ASE, influences individuals' perception, muscular activity, and exploratory movements. ASEs are engineered to offer support, alleviate fatigue, and optimize the wearer's performance, particularly for tasks requiring the lifting of heavy loads or sustained activity with arms raised over extended periods. Experiment 2 demonstrated a pattern of results for perceived heaviness that are consistent with those observed in experiment 1.

Movement control and coordination

> "Producing "bab" is one synergy of the muscles of tongue, lips, and jaw. But the same muscles and articulators, the same subsystems or degrees of freedom, can most obviously be called upon to produce other syllables." – Turvey (2007).

Traditionally, movement coordination has been studied by considering anatomical components as separate entities with many degrees of freedom that need to be controlled by a central executive (Rosenbaum, 2009). Controlling such a system by individually focusing on each component would be a cumbersome task. Instead, the human body could couple together several of these degrees of freedom based on the constraints in the environment and the intended goal to be achieved (Gray, 2020).

One key feature of humans is our remarkable ability to adapt to changes in our environment and perceive affordances. To do this, we control and coordinate our movements. Whether individuals are attempting to perceive the heaviness or length of an object they are wielding, the same muscles and body segments may be involved and coordinate with each other. However, as Turvey (2007) suggests, this coordination involves more of a soft assembly than a hard one. To achieve different functional goals, the same set of units can work together such that different types of synergies emerge.

Experiment 1 demonstrated that specific intentions could lead to specific movements and muscular activity to pick up invariant information that specifies the corresponding affordance. This provides evidence for the co-specificity hypothesis (Arzamarski et al., 2010; Riley et al., 2002). Even when participants wore an external device like an ASE, they were still able to perceive affordances, albeit with different movements and muscular activity, indicating the flexibility of the human musculoskeletal system.

Although previous studies indicate that ASEs could restrict movements while performing tasks above shoulder level (Raveendranath et al., 2024; Smets, 2018), the results of experiment 2 indicate that participants still perceived differences in heaviness, even in the case where the same weight was attached farther from the grip position. Although participants in experiment 1 and 2 perceived the relative differences in heaviness as per the different conditions presented to them, the pattern of movements and muscle activity seem to be different. Further analysis needs to be done to confirm this and understand what these differences are. However, in both experiments, the pattern of muscular activity seems to be more deterministic, stationary, and stable when participants wielded rods with weights attached symmetrically as compared to asymmetrically. While exploratory movements were more deterministic and stable when weights were attached closer to the gripping position in experiment 1, such differences were not found in experiment 2. The fact that people perceived differences in heaviness based on the weight position even with no difference in muscular activity between these conditions suggests the flexibility in perceiving affordances. It is possible that there are factors related to body posture, or the activity of other muscles involved in wielding rods above shoulder level, which has not been explored in the current study, could play a role in helping people perceive such subtle differences in heaviness based on increased moment of inertia. Whether people can perceive heaviness more accurately even when they wear an ASE, and whether they can use haptic feedback to calibrate their movements and muscle activity to perceive such affordances more accurately needs to be explored in future studies.

As indicated by the results of the current study, the muscles and joints in our upper body work together, freezing the degrees of freedom to achieve specific goals. This is in line with the tensegrity hypothesis proposed by Turvey & Fonseca (2014), where the entire body is considered to be the medium for haptic perception. Dynamic touch works primarily based on tissue deformation. Changes in one part of the body caused by a perturbation will reflect in other areas as well. The current study was an attempt to understand the dynamics of muscular activity and upper body movements, under perturbations caused by wielding rods with different characteristics. However, if the tensegrity hypothesis holds true, such differences in dynamics should also be visible in how people control their posture (Mangalam et al., 2019; Mangalam et al., 2020; Palatinus et al., 2014). For instance, Mangalam et al. (2020) demonstrated that the fractal patterns detected in center of pressure measurements during participants' engagement in a dynamic touch task could accurately predict their intention to perceive either the length or weight of the rod in unimanual wielding.

Practical implications

In industrial settings, tasks often involve the ability to perceive affordances such as whether one can fit an object through an aperture or not, whether one can lift a load without resulting in any musculoskeletal damage, and so on. To help people successfully perform such tasks, it is important that scientists understand how people perceive such affordances, and what kinds of exploratory activities help them achieve this. Previous studies on bimanual lifts using exoskeletons have used ASEs as well as back-support exoskeletons (Alemi et al., 2020; Gillette & Stephenson, 2018; Madinei et al., 2020; Smets, 2018). Although these studies indicate that exoskeletons reduce the stress on muscles, none of these studies have explored the coordinated activity between muscles that are known to play a role in perceiving heaviness of hand-held objects. To fill this gap in literature, the main goal of experiment 2 was to understand such coordination as people wear an ASE and try to judge the heaviness of hand-held objects. It is hoped that by understanding how the human body achieves this task, engineers, designers, and scientists will be better able to incorporate exoskeletons into the body's tensegrity structure and facilitate its integration into the natural motor synergies (Profeta & Turvey, 2018).

The co-specificity hypothesis posits that an organism's intention, exploration, and the information specifying the property it intends to perceive are tightly linked. In the current study, it was observed that distinct exploratory movements are exhibited by individuals when they intend to perceive the heaviness of a rod compared to when they intend to perceive its length. These findings suggest that intentionality plays a crucial role in shaping exploratory movements and perception. Importantly, these insights hold significant implications for the field of robotics, where assistive robots can be designed to understand human intentions based on observed exploratory movements. By integrating the co-specificity hypothesis into robotic design, we can enhance the ability of a robot to interpret human intentions and adapt its actions accordingly. This could lead to the development of more intuitive and responsive robotic systems capable of effectively interacting with and assisting humans in various tasks.

Limitations

While the current study yields valuable insights into the perception of heaviness and length during rod wielding tasks, some limitations warrant acknowledgment. First, the study did not directly compare individuals wearing exoskeletons to those not wearing them, thus restricting the assessment of exoskeletons' influence on perception and exploratory movements. Moreover, although the weight perception task in experiment 1 involved manipulating the magnitude of weights, the rods' lengths remained constant for both the weight and length perception tasks, posing a limitation to the study's design. Furthermore, participants were granted the freedom to heft and wield the rods, rendering it challenging to discern the specific muscles or movements contributing to the perception of heaviness or length. Additionally, the duration of time participants wielded each rod was not standardized across experiments, introducing variability that could impact the results. Lastly, the study did not account for potential differences in perception or exploratory movements based on participants' sex or other individual differences in physical capacity, which could have implications for the generalizability of the findings. Further, the relationships investigated here may be altered when substantially heavier objects are being lifted.

Future work

MdRQA, a nonlinear analytical technique was used to analyze most of the data in the two experiments. Although this captures the dynamics in the pattern of exploratory wielding, other linear measures might also differentiate between the different perceptual intents, weight distributions, positions, and magnitudes. For example, perhaps the average angular acceleration of the body segments might be different for these different conditions. Such possibilities with linear measures were not investigated in the current study. Future analyses on the dataset from these experiments will explore such differences if they exist.

Future research on dynamic touch should explore bimanual wielding tasks more thoroughly. It promotes ergonomic design of workplaces and tasks, by understanding how individuals perceive and interact with their environment. This is essential for creating tools like exoskeletons that promote safety, efficiency, and comfort as well. One avenue for future investigation involves exploring length perception in bimanual wielding tasks, employing rods of varying lengths and weights to explain the role of the inertia tensor in direct perception. Additionally, further inquiry into the effects of wearing exoskeletons on affordance perception and calibration is required, as these devices increasingly find applications in various domains. By examining how individuals perceive the heaviness and length of hand-held objects while wearing an exoskeleton, and exploring the co-specificity hypothesis with the exoskeletons, researchers can shed light on the extent to which the design of such devices can be improved to accommodate the intentions of the wearer. Moreover, future studies should extend the investigation of the tensegrity hypothesis beyond local muscles which are in direct contact with the hand-held objects, and movements of the upper arm. More distant features such as body posture which could play a role in perceiving affordances should be incorporated in such investigations. By exploring the dynamic interplay between various body segments and their role in perception and action, researchers can gain insights into the holistic nature of motor control.

APPENDICES

Appendix A

The R code for processing data

```
#Reading maximum voluntary contraction values
mvc<-read.csv("D:/Exo/Dissertation/Participant data/MVC.csv")
UpperTrapezius_RT_max <- mvc$UpperTrapezius_RT_max
UpperTrapezius_LT_max <- mvc$UpperTrapezius_LT_max
AnteriorDeltoid_RT_max <- mvc$AnteriorDeltoid_RT_max
AnteriorDeltoid_LT_max <- mvc$AnteriorDeltoid_LT_max
BicepsBrachii_RT_max <- mvc$BicepsBrachii_RT_max
BicepsBrachii_LT_max <- mvc$BicepsBrachii_LT_max
FlexorCarpiRadialis_RT_max <- mvc$FlexorCarpiRadialis_RT_max
FlexorCarpiRadialis_LT_max <- mvc$FlexorCarpiRadialis_LT_max
FlexorCarpiUlnaris_RT_max <- mvc$FlexorCarpiUlnaris_RT_max
FlexorCarpiUlnaris_LT_max <- mvc$FlexorCarpiUlnaris_LT_max
library(dplyr) #used to process and filter data
trialnumber <- c(1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60)
#normalizing EMG data for each muscle
for (p in trialnumber){
    path <- paste0("D:/Exo/Dissertation/Participant data/Trials_filtered_with_heading/Length_Trial",p, ".csv")
    dat<-read.csv(file = path)
    dat <- dat %>% mutate(UpperTrapezius_RT_norm = (UpperTrapezius_RT/UpperTrapezius_RT_max)*100)
    dat <- dat %>% mutate(UpperTrapezius_LT_norm = (UpperTrapezius_LT/UpperTrapezius_LT_max)*100)
    dat <- dat %>% mutate(AnteriorDeltoid_RT_norm = (AnteriorDeltoid_RT/AnteriorDeltoid_RT_max)*100)
    dat <- dat %>% mutate(AnteriorDeltoid_LT_norm = (AnteriorDeltoid_LT/AnteriorDeltoid_LT_max)*100)
    dat <- dat %>% mutate(BicepsBrachii_RT_norm = (BicepsBrachii_RT/BicepsBrachii_RT_max)*100)
    dat <- dat %>% mutate(BicepsBrachii_LT_norm = (BicepsBrachii_LT/BicepsBrachii_LT_max)*100)
    dat <- dat %>% mutate(FlexorCarpiRadialis_RT_norm = (FlexorCarpiRadialis_RT/FlexorCarpiRadialis_RT_max)*100)
    dat <- dat %>% mutate(FlexorCarpiRadialis_LT_norm = (FlexorCarpiRadialis_LT/FlexorCarpiRadialis_LT_max)*100)
    dat <- dat %>% mutate(FlexorCarpiUlnaris_RT_norm = (FlexorCarpiUlnaris_RT/FlexorCarpiUlnaris_RT_max)*100)
    dat <- dat %>% mutate(FlexorCarpiUlnaris_LT_norm = (FlexorCarpiUlnaris_LT/FlexorCarpiUlnaris_LT_max)*100)
    path2 <- paste0("D:/Exo/Dissertation/Participant data/Trials_filtered_and_normalized/Length_Trial",p, "normalized.csv")
```

```
    write.csv(dat, file=path2, row.names = F)
}
```

The R code for statistical analysis

```
#R code and results for experiment 1

library(dplyr)  #used to process and filter the data
library(nlme)   #used to create linear mixed effects models
library(data.table) #used to create a dataframe from multiple excel she
ets
library(multilevel) #Used to compute icc

## Warning: package 'multilevel' was built under R version 4.1.2

library(MuMIn)      #Used to compute R squared values

## Warning: package 'MuMIn' was built under R version 4.1.3

library(emmeans)    #used for estimated marginal means
#Retrieving data
path <- "D:/Exo/Dissertation/Participant data/Analysis"
multmerge = function(path){
  filenames=list.files(path=path, full.names=TRUE)
  rbindlist(lapply(filenames, fread))
}
dat <- multmerge(path)
#splitting data based on perceptual intent
dat1 <- dat %>% filter(Intention == "Weight")
dat2 <- dat %>% filter(Intention == "Length")
#converting variables to factors
dat1$ParticipantID <- factor(dat1$ParticipantID)
dat1$Symmetry <- factor(dat1$Symmetry)
dat1$DistanceFromGrip <- factor(dat1$DistanceFromGrip)
dat1$WeightAttached <- factor(dat1$WeightAttached)
dat2$ParticipantID <- factor(dat1$ParticipantID)
dat2$Symmetry <- factor(dat1$Symmetry)
dat2$DistanceFromGrip <- factor(dat1$DistanceFromGrip)
dat2$WeightAttached <- factor(dat1$WeightAttached)
#Creating models for perceived Weight
model <- lme(PerceivedWeight ~ 1, data = dat1, method = "REML", na.acti
on = "na.omit", random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.3472809
##
## $Group
```

```
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9696262 0.9696262 0.9696262 0.9696262 0.9696262 0.9696262 0.9
696262
##  [8] 0.9696262 0.9696262 0.9696262 0.9696262 0.9696262 0.9696262 0.9
696262
## [15] 0.9696262 0.9696262
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(PerceivedWeight ~ Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat1, method = "REML", na.action = "na.omit", random = ~1
|ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF   F-value p-value
## (Intercept)          1   940  60.60500  <.0001
## Symmetry             1   940 160.57086  <.0001
## DistanceFromGrip     1   940   7.85383  0.0052
## WeightAttached       2   940 120.14482  <.0001
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##            R2m       R2c
## [1,] 0.1942969 0.5441053
```

```
#estimated marginal means based on the effect of each independent varia
ble
emmeans(model1,pairwise~Symmetry)
```

```
## $emmeans
##  Symmetry   emmean   SE df lower.CL upper.CL
##  Asymmetric    241 21.6 15      195      287
##  Symmetric     163 21.6 15      117      209
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment
```

```
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate   SE  df t.ratio p.value
##  Asymmetric - Symmetric     78.9 6.23 940  12.672  <.0001
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~DistanceFromGrip)
```

```
## $emmeans
##  DistanceFromGrip emmean   SE df lower.CL upper.CL
##  10                  193 21.6 15      147      239
##  20                  211 21.6 15      165      257
##
## Results are averaged over the levels of: Symmetry, WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate   SE  df t.ratio p.value
##  10 - 20     -17.5 6.23 940  -2.802  0.0052
##
## Results are averaged over the levels of: Symmetry, WeightAttached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~WeightAttached)
```

```
## $emmeans
##  WeightAttached emmean   SE df lower.CL upper.CL
##  1                 142 21.8 15       96      189
##  2                 203 21.8 15      156      249
##  3                 261 21.8 15      214      307
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate   SE  df t.ratio p.value
##  1 - 2       -60.5 7.63 940  -7.930  <.0001
##  1 - 3      -118.2 7.63 940 -15.500  <.0001
##  2 - 3       -57.7 7.63 940  -7.570  <.0001
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
```

```
## P value adjustment: tukey method for comparing a family of 3 estimat
es

#Model with two-way interactions
model2 <- lme(PerceivedWeight ~ Symmetry + DistanceFromGrip + WeightAtt
ached +Symmetry:DistanceFromGrip, data = dat1, method = "ML", na.action
= "na.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                            numDF denDF   F-value p-value
## (Intercept)                    1   939  53.23519  <.0001
## Symmetry                       1   939  34.89640  <.0001
## DistanceFromGrip               1   939  26.39459  <.0001
## WeightAttached                 2   939 122.41796  <.0001
## Symmetry:DistanceFromGrip      1   939  19.68483  <.0001

#Testing simple effects
simple.one <- lme(PerceivedWeight~Symmetry, subset=DistanceFromGrip=="1
0", dat1, method = "ML", na.action = "na.omit", random = ~1|Participant
ID)
simple.two <- lme(PerceivedWeight~Symmetry, subset=DistanceFromGrip=="2
0", dat1, method = "ML", na.action = "na.omit", random = ~1|Participant
ID)
summary(simple.one)

## Linear mixed-effects model fit by maximum likelihood
##   Data: dat1
##   Subset: DistanceFromGrip == "10"
##        AIC      BIC    logLik
##   5876.012 5892.707 -2934.006
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    77.28508 104.1522
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                        Value Std.Error  DF   t-value p-value
## (Intercept)        219.07917 20.500273 463 10.686646       0
## SymmetrySymmetric  -51.54583  9.527618 463 -5.410149       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.232
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -2.70048434 -0.41110678 -0.04159606  0.26197973  6.86088826
##
```

```
## Number of Observations: 480
## Number of Groups: 16

summary(simple.two)

## Linear mixed-effects model fit by maximum likelihood
##   Data: dat1
##   Subset: DistanceFromGrip == "20"
##        AIC      BIC    logLik
##   5932.646 5949.341 -2962.323
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    84.86414 110.3572
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                       Value Std.Error  DF   t-value p-value
## (Intercept)        263.9083  22.42678 463  11.76755       0
## SymmetrySymmetric -106.2958  10.09525 463 -10.52930       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.225
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.42748384 -0.51413410 -0.05858682  0.34921553  6.22483067
##
## Number of Observations: 480
## Number of Groups: 16

model2 <- lme(PerceivedWeight ~ Symmetry + DistanceFromGrip + WeightAtt
ached + Symmetry:WeightAttached, data = dat1, method = "ML", na.action
= "na.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                           numDF denDF  F-value p-value
## (Intercept)                   1   938 54.45536  <.0001
## Symmetry                      1   938 29.85844  <.0001
## DistanceFromGrip              1   938  7.89785  0.0051
## WeightAttached                2   938 84.45601  <.0001
## Symmetry:WeightAttached       2   938  4.07587  0.0173

simple.one <- lme(PerceivedWeight~Symmetry, subset=WeightAttached=="1",
dat1, method = "REML", na.action = "na.omit", random = ~1|ParticipantID
)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat1
##   Subset: WeightAttached == "1"
##        AIC      BIC    logLik
##   3709.867 3724.916 -1850.934
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    38.98804 76.92691
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                        Value Std.Error  DF  t-value p-value
## (Intercept)       171.85000  11.48870 303 14.95818       0
## SymmetrySymmetric -58.78125   8.60069 303 -6.83448       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.374
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -1.84556348 -0.40844908 -0.03431149  0.19125667  9.73669137
##
## Number of Observations: 320
## Number of Groups: 16
```

```
simple.two <- lme(PerceivedWeight~Symmetry, subset=WeightAttached=="2",
dat1, method = "REML", na.action = "na.omit", random = ~1|ParticipantID
)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat1
##   Subset: WeightAttached == "2"
##        AIC      BIC    logLik
##   3747.334 3762.382 -1869.667
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    84.17513 79.03688
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                      Value Std.Error  DF   t-value p-value
## (Intercept)       240.975 21.951843 303 10.977438       0
## SymmetrySymmetric -76.050  8.836592 303 -8.606259       0
##  Correlation:
```

```
##                     (Intr)
## SymmetrySymmetric -0.201
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -2.5802291 -0.4729812 -0.0493862  0.2974348  7.7377428
##
## Number of Observations: 320
## Number of Groups: 16
```

```
simple.three <- lme(PerceivedWeight~Symmetry, subset=WeightAttached=="3
", dat1, method = "REML", na.action = "na.omit", random = ~1|Participan
tID)
summary(simple.three)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat1
##   Subset: WeightAttached == "3"
##        AIC      BIC    logLik
##   3951.797 3966.845 -1971.899
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    130.7822 108.3895
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                        Value Std.Error  DF   t-value p-value
## (Intercept)         311.6562  33.79979 303  9.220657       0
## SymmetrySymmetric -101.9313  12.11832 303 -8.411335       0
##  Correlation:
##                     (Intr)
## SymmetrySymmetric -0.179
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -2.57272964 -0.42262221 -0.06235642  0.33662367  5.69391627
##
## Number of Observations: 320
## Number of Groups: 16
```

```
#Creating models for perceived Length
model <- lme(PerceivedLength ~ 1, data = dat2, method = "REML", na.acti
on = "na.omit", random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.4557781
```

```
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9804875 0.9804875 0.9804875 0.9804875 0.9804875 0.9804875 0.9
804875
##  [8] 0.9804875 0.9804875 0.9804875 0.9804875 0.9804875 0.9804875 0.9
804875
## [15] 0.9804875 0.9804875
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(PerceivedLength ~ Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat2, method = "REML", na.action = "na.omit", random = ~1
|ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF denDF  F-value p-value
## (Intercept)          1   940 724.1923  <.0001
## Symmetry             1   940   1.1409  0.2857
## DistanceFromGrip     1   940   0.0028  0.9575
## WeightAttached       2   940   1.3931  0.2488

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##              R2m       R2c
## [1,] 0.002225274 0.4569704

#Model with two-way interactions
model2 <- lme(PerceivedLength ~ (Symmetry + DistanceFromGrip + WeightAt
tached)^2, data = dat2, method = "ML", na.action = "na.omit", random =
~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                                 numDF denDF  F-value p-value
## (Intercept)                         1   935 700.9080  <.0001
## Symmetry                            1   935   2.8970  0.0891
## DistanceFromGrip                    1   935   0.0549  0.8148
```

```
## WeightAttached                          2    935    0.0229   0.9774
## Symmetry:DistanceFromGrip               1    935    4.1732   0.0413
## Symmetry:WeightAttached                 2    935    0.0449   0.9561
## DistanceFromGrip:WeightAttached         2    935    0.8706   0.4190

#Analysis of MdRQA variables for EMG data in Experiment 1
#Retrieving data
path <- "D:/Exo/Dissertation/Participant data/EMGAnalysisMdRQA/"
multmerge = function(path){
  filenames=list.files(path=path, full.names=TRUE)
  rbindlist(lapply(filenames, fread))
}
dat <- multmerge(path)
#converting variables to factors
dat$ParticipantID <- factor(dat$ParticipantID)
dat$Intention <- factor(dat$Intention)
dat$Symmetry <- factor(dat$Symmetry)
dat$DistanceFromGrip <- factor(dat$DistanceFromGrip)
dat$WeightAttached <- factor(dat$WeightAttached)

#Creating models for determinance
model <- lme(DET ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.3983325
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 119 120 120 119 119 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9875693 0.9875693 0.9875693 0.9875693 0.9874661 0.9875693 0.9
875693
##  [8] 0.9874661 0.9874661 0.9875693 0.9875693 0.9875693 0.9875693 0.9
875693
## [15] 0.9875693 0.9875693
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(DET ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat, method = "REML", na.action = "na.omit", random = ~1|
ParticipantID)
```

```
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                   numDF denDF   F-value p-value
## (Intercept)           1  1896 289204526  <.0001
## Intention             1  1896        89  <.0001
## Symmetry              1  1896       302  <.0001
## DistanceFromGrip      1  1896         5  0.0214
## WeightAttached        2  1896         8  0.0003

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##             R2m       R2c
## [1,] 0.1037288 0.5179926

#estimated marginal means
emmeans(model1,pairwise~Intention)

## $emmeans
##  Intention emmean        SE df lower.CL upper.CL
##  Length    99.967 0.0057688 15   99.955   99.979
##  Weight    99.956 0.0057689 15   99.944   99.969
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast        estimate      SE   df t.ratio p.value
##  Length - Weight   0.0106 0.00113 1896   9.413  <.0001
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~Symmetry)

## $emmeans
##  Symmetry   emmean        SE df lower.CL upper.CL
##  Asymmetric 99.952 0.0057689 15   99.940   99.964
##  Symmetric  99.972 0.0057687 15   99.959   99.984
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
```

```
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate      SE   df t.ratio p.value
##  Asymmetric - Symmetric  -0.0196 0.00113 1896 -17.374  <.0001
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~DistanceFromGrip)
```

```
## $emmeans
##  DistanceFromGrip emmean        SE df lower.CL upper.CL
##  10               99.963 0.0057689 15   99.951   99.975
##  20               99.960 0.0057687 15   99.948   99.973
##
## Results are averaged over the levels of: Intention, Symmetry, Weight
Attached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate      SE   df t.ratio p.value
##  10 - 20   0.00259 0.00113 1896   2.304  0.0214
##
## Results are averaged over the levels of: Intention, Symmetry, Weight
Attached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~WeightAttached)
```

```
## $emmeans
##  WeightAttached emmean        SE df lower.CL upper.CL
##  1              99.965 0.0057962 15   99.952   99.977
##  2              99.962 0.0057964 15   99.949   99.974
##  3              99.959 0.0057961 15   99.947   99.971
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate      SE   df t.ratio p.value
##  1 - 2     0.00285 0.00138 1896   2.067  0.0969
##  1 - 3     0.00561 0.00138 1896   4.069  0.0001
```

```
##  2 - 3     0.00276 0.00138 1896   1.999  0.1128
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
#Model with two-way interactions
model2 <- lme(DET ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached + Intention:Symmetry, data = dat, method = "REML", na.action = "n
a.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')
```

```
##                      numDF  denDF    F-value  p-value
## (Intercept)              1   1895  286805127  <.0001
## Intention                1   1895        108  <.0001
## Symmetry                 1   1895         75  <.0001
## DistanceFromGrip         1   1895          5  0.0206
## WeightAttached           2   1895          8  0.0002
## Intention:Symmetry       1   1895         27  <.0001
```

```
#testing simple effects
simple.one <- lme(DET~Symmetry, subset=Intention=="Length", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Length"
##         AIC       BIC   logLik
##   -4633.876 -4614.421 2320.938
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:   0.0218166 0.02057404
##
## Fixed effects:  DET ~ Symmetry
##                        Value   Std.Error  DF   t-value p-value
## (Intercept)         99.96019 0.005534572 942 18061.053       0
## SymmetrySymmetric    0.01375 0.001328753 942    10.349       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.12
##
## Standardized Within-Group Residuals:
##         Min           Q1          Med           Q3          Max
```

```
## -17.1343853  -0.2968121   0.1059539   0.4527580   3.3524884
##
## Number of Observations: 959
## Number of Groups: 16
```

```r
simple.two <- lme(DET~Symmetry, subset=Intention=="Weight", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Weight"
##         AIC       BIC   logLik
##   -4175.286 -4155.835 2091.643
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:  0.02610557 0.02610734
##
## Fixed effects:  DET ~ Symmetry
##                       Value   Std.Error  DF   t-value p-value
## (Intercept)       99.94377 0.006634742 941 15063.701       0
## SymmetrySymmetric  0.02540 0.001687009 941    15.056       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.127
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -7.50264333 -0.36529136  0.06872235  0.55061861  2.75208990
##
## Number of Observations: 958
## Number of Groups: 16
```

```r
model2 <- lme(DET ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached + DistanceFromGrip:WeightAttached, data = dat, method = "REML", n
a.action = "na.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')
```

```
##                                 numDF denDF   F-value p-value
## (Intercept)                         1  1894 284016623  <.0001
## Intention                           1  1894        89  <.0001
## Symmetry                            1  1894       303  <.0001
## DistanceFromGrip                    1  1894         0  0.7357
## WeightAttached                      2  1894         1  0.2569
## DistanceFromGrip:WeightAttached     2  1894         3  0.0495
```

```r
simple.one <- lme(DET~DistanceFromGrip, subset=WeightAttached=="1", dat
, method = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "1"
##         AIC       BIC   logLik
##   -2881.376 -2863.549 1444.688
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:  0.02042037 0.02384682
##
## Fixed effects:  DET ~ DistanceFromGrip
##                         Value   Std.Error  DF   t-value p-value
## (Intercept)        99.96493 0.005276815 622 18944.180  0.0000
## DistanceFromGrip20 -0.00066 0.001886768 622    -0.351  0.7254
##  Correlation:
##                    (Intr)
## DistanceFromGrip20 -0.179
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -6.2727735 -0.2674706  0.2146590  0.5291609  3.1596576
##
## Number of Observations: 639
## Number of Groups: 16
```

```r
simple.two <- lme(DET~DistanceFromGrip, subset=WeightAttached=="2", dat
, method = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "2"
##         AIC       BIC  logLik
##   -2743.059 -2725.238 1375.53
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:  0.02227057 0.02650138
##
## Fixed effects:  DET ~ DistanceFromGrip
##                         Value   Std.Error  DF  t-value p-value
## (Intercept)        99.96214 0.005762595 621 17346.72   0.000
```

```
## DistanceFromGrip20 -0.00071 0.002098481 621    -0.34   0.734
##  Correlation:
##                     (Intr)
## DistanceFromGrip20 -0.183
##
## Standardized Within-Group Residuals:
##        Min          Q1         Med          Q3         Max
## -5.6809427 -0.2671520  0.2090327  0.5040343  2.6920965
##
## Number of Observations: 638
## Number of Groups: 16
```

```
simple.three <- lme(DET~DistanceFromGrip, subset=WeightAttached=="3", d
at, method = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.three)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "3"
##         AIC       BIC   logLik
##   -2580.667 -2562.834 1294.333
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:  0.02560001 0.03030265
##
## Fixed effects:  DET ~ DistanceFromGrip
##                        Value   Std.Error  DF  t-value p-value
## (Intercept)         99.96223 0.006620390 623 15099.15  0.0000
## DistanceFromGrip20 -0.00649 0.002395635 623    -2.71  0.0069
##  Correlation:
##                     (Intr)
## DistanceFromGrip20 -0.181
##
## Standardized Within-Group Residuals:
##         Min           Q1          Med           Q3          Max
## -11.1777522  -0.2582854   0.1822395   0.4519685   2.8723359
##
## Number of Observations: 640
## Number of Groups: 16
```

```
#Creating models for average diagonal line length
model <- lme(ADL ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.2752047
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 119 120 120 119 119 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9785242 0.9785242 0.9785242 0.9785242 0.9783476 0.9785242 0.9
785242
##  [8] 0.9783476 0.9783476 0.9785242 0.9785242 0.9785242 0.9785242 0.9
785242
## [15] 0.9785242 0.9785242
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(ADL ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat, method = "REML", na.action = "na.omit", random = ~1|
ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF   F-value p-value
## (Intercept)          1  1896 187.52007  <.0001
## Intention            1  1896  46.79510  <.0001
## Symmetry             1  1896 148.70894  <.0001
## DistanceFromGrip     1  1896   0.60233  0.4378
## WeightAttached       2  1896   4.95282  0.0072
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##             R2m       R2c
## [1,] 0.06906349 0.3576928
```

```
#estimated marginal means
emmeans(model1,pairwise~Intention)
```

```
## $emmeans
##  Intention emmean   SE df lower.CL upper.CL
##  Length       146 9.58 15      126      167
##  Weight       129 9.58 15      108      149
```

```
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast        estimate   SE   df t.ratio p.value
##  Length - Weight     17.5 2.56 1896   6.841  <.0001
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~Symmetry)
```

```
## $emmeans
##  Symmetry   emmean   SE df lower.CL upper.CL
##  Asymmetric    122 9.58 15      101      142
##  Symmetric     153 9.58 15      133      174
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate   SE   df t.ratio p.value
##  Asymmetric - Symmetric    -31.3 2.56 1896 -12.195  <.0001
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~WeightAttached)
```

```
## $emmeans
##  WeightAttached emmean   SE df lower.CL upper.CL
##  1                 142 9.67 15      121      162
##  2                 139 9.67 15      118      159
##  3                 132 9.67 15      111      153
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
```

```
##  contrast estimate   SE   df t.ratio p.value
##  1 - 2        2.94 3.14 1896   0.935  0.6180
##  1 - 3        9.64 3.14 1896   3.070  0.0061
##  2 - 3        6.70 3.14 1896   2.133  0.0835
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
#Model with two-way interactions
model2 <- lme(ADL ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached + Intention:Symmetry, data = dat, method = "REML", na.action = "n
a.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')
```

```
##                    numDF denDF   F-value p-value
## (Intercept)            1  1895 193.78569  <.0001
## Intention              1  1895  45.00100  <.0001
## Symmetry               1  1895  45.87752  <.0001
## DistanceFromGrip       1  1895   0.60205  0.4379
## WeightAttached         2  1895   4.97023  0.0070
## Intention:Symmetry     1  1895   6.96342  0.0084
```

```
#testing simple effects
simple.one <- lme(ADL~Symmetry, subset=Intention=="Length", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Length"
##       AIC      BIC    logLik
##   10298.1 10317.55 -5145.049
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    46.66117 50.39106
##
## Fixed effects:  ADL ~ Symmetry
##                        Value Std.Error  DF   t-value p-value
## (Intercept)        133.99067 11.890350 942 11.268859       0
## SymmetrySymmetric   24.55473  3.254453 942  7.544964       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.137
```

```
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -2.4458979 -0.6022279 -0.1332241  0.5202371  4.2313822
##
## Number of Observations: 959
## Number of Groups: 16
```

```
simple.two <- lme(ADL~Symmetry, subset=Intention=="Weight", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Weight"
##        AIC      BIC    logLik
##   10437.47 10456.92 -5214.735
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    38.44604 54.73631
##
## Fixed effects:  ADL ~ Symmetry
##                        Value Std.Error  DF  t-value p-value
## (Intercept)       109.75477  9.932240 941 11.05035       0
## SymmetrySymmetric  37.99405  3.536961 941 10.74201       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.178
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -2.1049161 -0.6317036 -0.1221650  0.4898136  7.8373394
##
## Number of Observations: 958
## Number of Groups: 16
```

```
#Creating models for maximum diagonal line length
model <- lme(MDL ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.5736951
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
```

```
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 119 120 120 119 119 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9938457 0.9938457 0.9938457 0.9938457 0.9937943 0.9938457 0.9
938457
##  [8] 0.9937943 0.9937943 0.9938457 0.9938457 0.9938457 0.9938457 0.9
938457
## [15] 0.9938457 0.9938457
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(MDL ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat, method = "REML", na.action = "na.omit", random = ~1|
ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF denDF  F-value p-value
## (Intercept)          1  1896 64.89228  <.0001
## Intention            1  1896  9.29390  0.0023
## Symmetry             1  1896 22.69475  <.0001
## DistanceFromGrip     1  1896  3.10738  0.0781
## WeightAttached       2  1896  2.28793  0.1018

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##              R2m       R2c
## [1,] 0.008349975 0.5972939

#estimated marginal means
emmeans(model1,pairwise~Intention)

## $emmeans
##  Intention emmean   SE df lower.CL upper.CL
##  Length     14179 1740 15    10470    17889
##  Weight     13382 1740 15     9673    17092
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
```

```
##
## $contrasts
##  contrast        estimate  SE   df t.ratio p.value
##  Length - Weight      797 261 1896   3.049  0.0023
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~Symmetry)

## $emmeans
##  Symmetry   emmean   SE df lower.CL upper.CL
##  Asymmetric  14404 1740 15    10694    18113
##  Symmetric   13158 1740 15     9449    16867
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate  SE   df t.ratio p.value
##  Asymmetric - Symmetric     1246 261 1896   4.764  <.0001
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment

#Model with two-way interactions
model2 <- lme(MDL ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached + Intention:Symmetry, data = dat, method = "REML", na.action = "n
a.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                    numDF denDF  F-value p-value
## (Intercept)            1  1895 62.10841  <.0001
## Intention              1  1895  0.49241  0.4829
## Symmetry               1  1895  3.68559  0.0550
## DistanceFromGrip       1  1895  3.10883  0.0780
## WeightAttached         2  1895  2.29818  0.1007
## Intention:Symmetry     1  1895  4.22203  0.0400

#testing simple effects
simple.one <- lme(MDL~Symmetry, subset=Intention=="Length", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Length"
##        AIC      BIC    logLik
##   19055.57 19075.02 -9523.785
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    7768.289 4850.355
##
## Fixed effects:  MDL ~ Symmetry
##                       Value Std.Error  DF   t-value p-value
## (Intercept)       14531.453  1954.677 942  7.434198  0.0000
## SymmetrySymmetric  -706.826   313.255 942 -2.256392  0.0243
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.08
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.78617910 -0.49264564 -0.09571442  0.36184486  6.98067171
##
## Number of Observations: 959
## Number of Groups: 16
```

```
simple.two <- lme(MDL~Symmetry, subset=Intention=="Weight", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Weight"
##        AIC      BIC    logLik
##   19179.93 19199.38 -9585.967
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    7126.372 5243.682
##
## Fixed effects:  MDL ~ Symmetry
##                       Value Std.Error  DF   t-value p-value
## (Intercept)       14260.233 1797.6654 941  7.932641       0
## SymmetrySymmetric -1768.575  338.8373 941 -5.219540       0
##  Correlation:
##                   (Intr)
```

```
## SymmetrySymmetric -0.094
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -4.1408005 -0.5210136 -0.1047088  0.3479533  5.3539385
##
## Number of Observations: 958
## Number of Groups: 16
```

```
#Creating models for entropy
model <- lme(DENTR ~ 1, data = dat, method = "ML", na.action = "na.omit
", random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.4443208
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 119 120 120 119 119 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9896856 0.9896856 0.9896856 0.9896856 0.9895998 0.9896856 0.9
896856
##  [8] 0.9895998 0.9895998 0.9896856 0.9896856 0.9896856 0.9896856 0.9
896856
## [15] 0.9896856 0.9896856
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(DENTR ~ Intention + Symmetry + DistanceFromGrip + WeightA
ttached, data = dat, method = "REML", na.action = "na.omit", random = ~
1|ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF   F-value p-value
## (Intercept)          1  1896 1185.3758  <.0001
## Intention            1  1896    3.1867  0.0744
## Symmetry             1  1896   92.7609  <.0001
## DistanceFromGrip     1  1896    4.5412  0.0332
## WeightAttached       2  1896    4.6285  0.0099
```

```r
#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##              R2m       R2c
## [1,] 0.02925986 0.4894256

#estimated marginal means
emmeans(model1,pairwise~Symmetry)

## $emmeans
##  Symmetry   emmean    SE df lower.CL upper.CL
##  Asymmetric   9.12 0.255 15     8.58     9.66
##  Symmetric    8.65 0.255 15     8.11     9.19
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate     SE   df t.ratio p.value
##  Asymmetric - Symmetric    0.468 0.0485 1896   9.631  <.0001
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~DistanceFromGrip)

## $emmeans
##  DistanceFromGrip emmean    SE df lower.CL upper.CL
##  10                 8.83 0.255 15     8.29     9.38
##  20                 8.94 0.255 15     8.39     9.48
##
## Results are averaged over the levels of: Intention, Symmetry, Weight
Attached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE   df t.ratio p.value
##  10 - 20    -0.103 0.0485 1896  -2.131  0.0332
##
## Results are averaged over the levels of: Intention, Symmetry, Weight
```

```
Attached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~WeightAttached)

## $emmeans
##  WeightAttached emmean    SE df lower.CL upper.CL
##  1                8.78 0.256 15     8.24     9.33
##  2                8.91 0.256 15     8.37     9.46
##  3                8.96 0.256 15     8.41     9.50
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE   df t.ratio p.value
##  1 - 2     -0.1267 0.0595 1896  -2.131  0.0840
##  1 - 3     -0.1751 0.0594 1896  -2.946  0.0091
##  2 - 3     -0.0484 0.0595 1896  -0.814  0.6947
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es

#Model with two-way interactions
model2 <- lme(DENTR ~ Intention + Symmetry + DistanceFromGrip + WeightA
ttached + Intention:Symmetry, data = dat, method = "REML", na.action =
"na.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                    numDF denDF   F-value p-value
## (Intercept)            1  1895 1152.9682  <.0001
## Intention              1  1895   14.0520  0.0002
## Symmetry               1  1895   18.9354  <.0001
## DistanceFromGrip       1  1895    4.5603  0.0328
## WeightAttached         2  1895    4.6678  0.0095
## Intention:Symmetry     1  1895   12.3166  0.0005

#testing simple effects
simple.one <- lme(DENTR~Symmetry, subset=Intention=="Length", dat, meth
od = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Length"
##        AIC      BIC    logLik
##   2619.784 2639.239 -1305.892
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)  Residual
## StdDev:    1.086336 0.9086553
##
## Fixed effects:  DENTR ~ Symmetry
##                          Value  Std.Error  DF   t-value p-value
## (Intercept)         8.990256 0.27473932 942 32.72286       0
## SymmetrySymmetric -0.297636 0.05868453 942 -5.07179       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.107
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.27326945 -0.60929972 -0.03754104  0.56112072  5.87613531
##
## Number of Observations: 959
## Number of Groups: 16
```

```
simple.two <- lme(DENTR~Symmetry, subset=Intention=="Weight", dat, meth
od = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Weight"
##        AIC      BIC    logLik
##   2832.094 2851.545 -1412.047
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    1.129863 1.017955
##
## Fixed effects:  DENTR ~ Symmetry
##                          Value  Std.Error  DF   t-value p-value
## (Intercept)         9.245614 0.28627772 941 32.29596       0
## SymmetrySymmetric -0.635934 0.06577843 941 -9.66782       0
##  Correlation:
##                   (Intr)
```

```
## SymmetrySymmetric -0.115
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -2.42600915 -0.70857651 -0.02650259  0.59473574  4.16983941
##
## Number of Observations: 958
## Number of Groups: 16
```

```
#Creating models for laminarity
model <- lme(LAM ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.3755007
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 119 120 120 119 119 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9863302 0.9863302 0.9863302 0.9863302 0.9862169 0.9863302 0.9
863302
##  [8] 0.9862169 0.9862169 0.9863302 0.9863302 0.9863302 0.9863302 0.9
863302
## [15] 0.9863302 0.9863302
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(LAM ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat, method = "REML", na.action = "na.omit", random = ~1|
ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF   F-value p-value
## (Intercept)          1  1896 826188774  <.0001
## Intention            1  1896        83  <.0001
## Symmetry             1  1896       297  <.0001
## DistanceFromGrip     1  1896         7  0.0088
## WeightAttached       2  1896        10  <.0001
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##             R2m       R2c
## [1,] 0.1067745 0.4979711

#estimated marginal means
emmeans(model1,pairwise~Intention)

## $emmeans
##  Intention emmean        SE df lower.CL upper.CL
##  Length    99.982 0.0034074 15   99.974   99.989
##  Weight    99.975 0.0034074 15   99.968   99.983
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast        estimate       SE   df t.ratio p.value
##  Length - Weight  0.00637 0.000698 1896   9.126  <.0001
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~Symmetry)

## $emmeans
##  Symmetry   emmean        SE df lower.CL upper.CL
##  Asymmetric 99.972 0.0034074 15   99.965   99.980
##  Symmetric  99.984 0.0034073 15   99.977   99.992
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate       SE   df t.ratio p.value
##  Asymmetric - Symmetric   -0.012 0.000698 1896 -17.228  <.0001
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
```

```
, WeightAttached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~DistanceFromGrip)

## $emmeans
##  DistanceFromGrip emmean        SE df lower.CL upper.CL
##  10               99.979 0.0034074 15   99.972   99.987
##  20               99.978 0.0034073 15   99.970   99.985
##
## Results are averaged over the levels of: Intention, Symmetry, Weight
Attached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate       SE   df t.ratio p.value
##  10 - 20   0.00183 0.000698 1896   2.621  0.0088
##
## Results are averaged over the levels of: Intention, Symmetry, Weight
Attached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~WeightAttached)

## $emmeans
##  WeightAttached emmean        SE df lower.CL upper.CL
##  1              99.980 0.0034252 15   99.973   99.988
##  2              99.978 0.0034253 15   99.971   99.986
##  3              99.976 0.0034251 15   99.969   99.984
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate       SE   df t.ratio p.value
##  1 - 2     0.00194 0.000855 1896   2.274  0.0598
##  1 - 3     0.00387 0.000854 1896   4.529  <.0001
##  2 - 3     0.00193 0.000855 1896   2.253  0.0629
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```r
#Model with two-way interactions
model2 <- lme(LAM ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached + Intention:Symmetry, data = dat, method = "REML", na.action = "n
a.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')
```

```
##                      numDF denDF   F-value p-value
## (Intercept)              1  1895 818695596  <.0001
## Intention                1  1895       107  <.0001
## Symmetry                 1  1895        71  <.0001
## DistanceFromGrip         1  1895         7  0.0084
## WeightAttached           2  1895        10  <.0001
## Intention:Symmetry       1  1895        30  <.0001
```

```r
#testing simple effects
simple.one <- lme(LAM~Symmetry, subset=Intention=="Length", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Length"
##         AIC       BIC   logLik
##   -5556.414 -5536.959 2782.207
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:  0.01287754 0.01271451
##
## Fixed effects:  LAM ~ Symmetry
##                        Value   Std.Error  DF   t-value p-value
## (Intercept)         99.97747 0.003271382 942 30561.231       0
## SymmetrySymmetric    0.00827 0.000821153 942    10.065       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.126
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -17.4551621  -0.3063723   0.1095779   0.4700019   2.9988819
##
## Number of Observations: 959
## Number of Groups: 16
```

```r
simple.two <- lme(LAM~Symmetry, subset=Intention=="Weight", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Weight"
##         AIC       BIC   logLik
##   -5100.018 -5080.567 2554.009
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:  0.01567277 0.01610269
##
## Fixed effects:  LAM ~ Symmetry
##                         Value   Std.Error  DF   t-value p-value
## (Intercept)       99.96734 0.003986818 941 25074.466       0
## SymmetrySymmetric  0.01579 0.001040527 941    15.178       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.131
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -7.46872186 -0.40644814  0.08044879  0.59786100  2.85347571
##
## Number of Observations: 958
## Number of Groups: 16
```

```
model2 <- lme(LAM ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached + DistanceFromGrip:WeightAttached, data = dat, method = "ML", na.
action = "na.omit", random = ~1|ParticipantID)
#testing simple effects
simple.one <- lme(LAM~DistanceFromGrip, subset=WeightAttached=="1", dat
, method = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "1"
##        AIC       BIC  logLik
##   -3494.54 -3476.713 1751.27
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:  0.01200667 0.01475406
##
## Fixed effects:  LAM ~ DistanceFromGrip
##                          Value   Std.Error  DF  t-value p-value
```

```
## (Intercept)        99.98065 0.003113271 622 32114.34  0.0000
## DistanceFromGrip20 -0.00058 0.001167346 622    -0.50  0.6186
##  Correlation:
##                    (Intr)
## DistanceFromGrip20 -0.188
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -6.1894200 -0.2934610  0.2318651  0.5344802  3.3569698
##
## Number of Observations: 639
## Number of Groups: 16
```

```
simple.two <- lme(LAM~DistanceFromGrip, subset=WeightAttached=="2", dat
, method = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "2"
##         AIC       BIC   logLik
##   -3375.036 -3357.216 1691.518
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:   0.0131393 0.01613639
##
## Fixed effects:  LAM ~ DistanceFromGrip
##                       Value   Std.Error  DF   t-value p-value
## (Intercept)        99.97877 0.003407197 621 29343.405  0.0000
## DistanceFromGrip20 -0.00067 0.001277741 621    -0.521  0.6025
##  Correlation:
##                    (Intr)
## DistanceFromGrip20 -0.188
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -5.6451387 -0.2894299  0.1990033  0.5661846  2.5723938
##
## Number of Observations: 638
## Number of Groups: 16
```

```
simple.three <- lme(LAM~DistanceFromGrip, subset=WeightAttached=="3", d
at, method = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.three)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "3"
##        AIC       BIC  logLik
##   -3183.12 -3165.287 1595.56
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)   Residual
## StdDev:  0.01516754 0.01892121
##
## Fixed effects:  LAM ~ DistanceFromGrip
##                          Value    Std.Error  DF  t-value p-value
## (Intercept)          99.97863 0.003936646 623 25396.91  0.0000
## DistanceFromGrip20 -0.00429 0.001495853 623    -2.87  0.0042
##  Correlation:
##                      (Intr)
## DistanceFromGrip20 -0.19
##
## Standardized Within-Group Residuals:
##         Min           Q1          Med           Q3          Max
## -11.2954065  -0.2967511   0.1805519   0.4877821   2.7430234
##
## Number of Observations: 640
## Number of Groups: 16

#Analysis of MdRQA variables for kinematics data in Experiment 1

#Retrieving data
path <- "D:/Exo/Dissertation/Participant data/KinematicsAnalysisMdRQA/"
multmerge = function(path){
  filenames=list.files(path=path, full.names=TRUE)
  rbindlist(lapply(filenames, fread))
}
dat <- multmerge(path)
#converting variables to factors
dat$ParticipantID <- factor(dat$ParticipantID)
dat$Intention <- factor(dat$Intention)
dat$Symmetry <- factor(dat$Symmetry)
dat$DistanceFromGrip <- factor(dat$DistanceFromGrip)
dat$WeightAttached <- factor(dat$WeightAttached)

#Creating models for determinism
model <- lme(DET ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.1829887
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9641279 0.9641279 0.9641279 0.9641279 0.9641279 0.9641279 0.9
641279
##  [8] 0.9641279 0.9641279 0.9641279 0.9641279 0.9641279 0.9641279 0.9
641279
## [15] 0.9641279 0.9641279
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(DET ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat, method = "REML", na.action = "na.omit", random = ~1|
ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF  F-value p-value
## (Intercept)          1  1899 777.9958  <.0001
## Intention            1  1899  42.7263  <.0001
## Symmetry             1  1899   1.3477  0.2458
## DistanceFromGrip     1  1899   0.2574  0.6120
## WeightAttached       2  1899   0.6671  0.5133
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##             R2m       R2c
## [1,] 0.01875886 0.2116979
```

```
#estimated marginal means
emmeans(model1,pairwise~Intention)
```

```
## $emmeans
##  Intention emmean   SE df lower.CL upper.CL
##  Length      60.1 2.06 15     55.7     64.5
##  Weight      64.9 2.06 15     60.5     69.3
```

```
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast        estimate    SE   df t.ratio p.value
##  Length - Weight     -4.8 0.734 1899  -6.537  <.0001
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
```

```
#Model with two-way interactions
model2 <- lme(DET ~ (Intention + Symmetry + DistanceFromGrip + WeightAt
tached)^2, data = dat, method = "REML", na.action = "na.omit", random =
~1|ParticipantID)
anova.lme(model2, type = 'marginal')
```

```
##                                  numDF denDF  F-value p-value
## (Intercept)                          1  1890 586.8048  <.0001
## Intention                            1  1890   6.1973  0.0129
## Symmetry                             1  1890   0.9942  0.3188
## DistanceFromGrip                     1  1890   3.0640  0.0802
## WeightAttached                       2  1890   0.3581  0.6990
## Intention:Symmetry                   1  1890   1.0251  0.3114
## Intention:DistanceFromGrip           1  1890   1.0693  0.3012
## Intention:WeightAttached             2  1890   0.9930  0.3707
## Symmetry:DistanceFromGrip            1  1890   1.5439  0.2142
## Symmetry:WeightAttached              2  1890   2.5020  0.0822
## DistanceFromGrip:WeightAttached      2  1890   0.3238  0.7234
```

```
#Creating models for average diagonal line length
model <- lme(ADL ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.09156862
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120
##
```

```
## $MeanRel
##  [1] 0.9236398 0.9236398 0.9236398 0.9236398 0.9236398 0.9236398 0.9
236398
##  [8] 0.9236398 0.9236398 0.9236398 0.9236398 0.9236398 0.9236398 0.9
236398
## [15] 0.9236398 0.9236398
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(ADL ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat, method = "REML", na.action = "na.omit", random = ~1|
ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF  F-value p-value
## (Intercept)          1  1899 322.5520  <.0001
## Intention            1  1899  11.5235  0.0007
## Symmetry             1  1899   0.6278  0.4283
## DistanceFromGrip     1  1899   1.4495  0.2288
## WeightAttached       2  1899   1.4116  0.2440
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##              R2m       R2c
## [1,] 0.007659883 0.1050102
```

```
#estimated marginal means
emmeans(model1,pairwise~Intention)
```

```
## $emmeans
##  Intention emmean   SE df lower.CL upper.CL
##  Length      5.19 0.26 15     4.64     5.75
##  Weight      5.65 0.26 15     5.09     6.20
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast        estimate    SE   df t.ratio p.value
##  Length - Weight   -0.455 0.134 1899  -3.395  0.0007
##
```

```
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment

#Model with two-way interactions
model2 <- lme(ADL ~ (Intention + Symmetry + DistanceFromGrip + WeightAt
tached)^2, data = dat, method = "REML", na.action = "na.omit", random =
~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                                  numDF denDF   F-value p-value
## (Intercept)                          1  1890 184.41024  <.0001
## Intention                            1  1890   4.01098  0.0453
## Symmetry                             1  1890   1.68721  0.1941
## DistanceFromGrip                     1  1890   5.49269  0.0192
## WeightAttached                       2  1890   0.59623  0.5510
## Intention:Symmetry                   1  1890   1.08463  0.2978
## Intention:DistanceFromGrip           1  1890   0.11977  0.7293
## Intention:WeightAttached             2  1890   0.04077  0.9600
## Symmetry:DistanceFromGrip            1  1890   0.96005  0.3273
## Symmetry:WeightAttached              2  1890   0.76514  0.4654
## DistanceFromGrip:WeightAttached      2  1890   1.85195  0.1572

#Creating models for maximum diagonal line length
model <- lme(MDL ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.2696148
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9779234 0.9779234 0.9779234 0.9779234 0.9779234 0.9779234 0.9
779234
##  [8] 0.9779234 0.9779234 0.9779234 0.9779234 0.9779234 0.9779234 0.9
779234
## [15] 0.9779234 0.9779234
##
## attr(,"class")
## [1] "gmeanrel"
```

```r
model1 <- lme(MDL ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat, method = "REML", na.action = "na.omit", random = ~1|
ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF denDF   F-value p-value
## (Intercept)          1  1899 133.75182  <.0001
## Intention            1  1899   5.45067  0.0197
## Symmetry             1  1899   3.54843  0.0598
## DistanceFromGrip     1  1899   1.82888  0.1764
## WeightAttached       2  1899   2.68238  0.0687

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##              R2m       R2c
## [1,] 0.006005299 0.2883123

#estimated marginal means
emmeans(model1,pairwise~Intention)

## $emmeans
##  Intention emmean   SE df lower.CL upper.CL
##  Length      90.7 8.12 15     73.4      108
##  Weight      85.4 8.12 15     68.1      103
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast        estimate   SE   df t.ratio p.value
##  Length - Weight     5.38 2.31 1899   2.335  0.0197
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment

#Model with two-way interactions
model2 <- lme(MDL ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached + Intention:WeightAttached, data = dat, method = "REML", na.actio
n = "na.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')
```

```
##                              numDF denDF   F-value p-value
## (Intercept)                      1  1897 143.38793  <.0001
## Intention                        1  1897  16.06621  0.0001
## Symmetry                         1  1897   3.56463  0.0592
## DistanceFromGrip                 1  1897   1.83723  0.1754
## WeightAttached                   2  1897   6.95765  0.0010
## Intention:WeightAttached         2  1897   5.33352  0.0049
```

```
#testing simple effects
simple.one <- lme(MDL~Intention, subset=WeightAttached=="1", dat, metho
d = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "1"
##        AIC      BIC    logLik
##   6897.828 6915.662 -3444.914
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:     33.8425 51.28112
##
## Fixed effects:  MDL ~ Intention
##                      Value Std.Error  DF   t-value p-value
## (Intercept)       99.16250  8.933094 623 11.100578   0e+00
## IntentionWeight  -15.96875  4.054129 623 -3.938886   1e-04
##  Correlation:
##                 (Intr)
## IntentionWeight -0.227
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -1.8522128 -0.5942950 -0.1766520  0.3664742  6.9641544
##
## Number of Observations: 640
## Number of Groups: 16
```

```
simple.two <- lme(MDL~Intention, subset=WeightAttached=="2", dat, metho
d = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "2"
##       AIC      BIC   logLik
##   6988.54 7006.373 -3490.27
```

```
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    33.09561 55.17584
##
## Fixed effects:  MDL ~ Intention
##                    Value Std.Error  DF  t-value p-value
## (Intercept)     87.99375  8.830125 623 9.965176  0.0000
## IntentionWeight  0.68438  4.362033 623 0.156894  0.8754
##  Correlation:
##                 (Intr)
## IntentionWeight -0.247
##
## Standardized Within-Group Residuals:
##        Min          Q1         Med          Q3         Max
## -2.3297355 -0.5619554 -0.1382993  0.3269437 11.0275593
##
## Number of Observations: 640
## Number of Groups: 16
```

```
simple.three <- lme(MDL~Intention, subset=WeightAttached=="3", dat, met
hod = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.three)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "3"
##        AIC      BIC    logLik
##   6695.159 6712.992 -3343.579
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    29.02815 43.74461
##
## Fixed effects:  MDL ~ Intention
##                   Value Std.Error  DF   t-value p-value
## (Intercept)     85.0875  7.657975 623 11.110966  0.0000
## IntentionWeight -0.8625  3.458315 623 -0.249399  0.8031
##  Correlation:
##                 (Intr)
## IntentionWeight -0.226
##
## Standardized Within-Group Residuals:
##        Min          Q1         Med          Q3         Max
## -2.1778837 -0.6514345 -0.1923106  0.4472966  5.1679120
```

```
##
## Number of Observations: 640
## Number of Groups: 16
```

```
#Creating models for entropy
model <- lme(DENTR ~ 1, data = dat, method = "ML", na.action = "na.omit
", random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.4913287
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9914463 0.9914463 0.9914463 0.9914463 0.9914463 0.9914463 0.9
914463
##  [8] 0.9914463 0.9914463 0.9914463 0.9914463 0.9914463 0.9914463 0.9
914463
## [15] 0.9914463 0.9914463
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(DENTR ~ Intention + Symmetry + DistanceFromGrip + WeightA
ttached, data = dat, method = "REML", na.action = "na.omit", random = ~
1|ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF  F-value p-value
## (Intercept)          1  1899 740.8776  <.0001
## Intention            1  1899  21.5212  <.0001
## Symmetry             1  1899  28.6090  <.0001
## DistanceFromGrip     1  1899   4.6772  0.0307
## WeightAttached       2  1899   5.6605  0.0035
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##              R2m       R2c
## [1,] 0.01641979 0.5235097
```

```r
#estimated marginal means
emmeans(model1,pairwise~Intention)
```

```
## $emmeans
##  Intention emmean   SE df lower.CL upper.CL
##  Length      6.10 0.22 15     5.63     6.57
##  Weight      5.92 0.22 15     5.45     6.39
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast        estimate     SE   df t.ratio p.value
##  Length - Weight    0.179 0.0387 1899   4.639  <.0001
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
```

```r
emmeans(model1,pairwise~Symmetry)
```

```
## $emmeans
##  Symmetry   emmean   SE df lower.CL upper.CL
##  Asymmetric   6.11 0.22 15     5.64     6.58
##  Symmetric    5.91 0.22 15     5.44     6.37
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate     SE   df t.ratio p.value
##  Asymmetric - Symmetric    0.207 0.0387 1899   5.349  <.0001
##
## Results are averaged over the levels of: Intention, DistanceFromGrip
, WeightAttached
## Degrees-of-freedom method: containment
```

```r
emmeans(model1,pairwise~DistanceFromGrip)
```

```
## $emmeans
##  DistanceFromGrip emmean   SE df lower.CL upper.CL
```

```
##  10                   5.97 0.22 15     5.50     6.44
##  20                   6.05 0.22 15     5.58     6.52
##
## Results are averaged over the levels of: Intention, Symmetry, Weight
Attached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE   df t.ratio p.value
##  10 - 20   -0.0836 0.0387 1899  -2.163  0.0307
##
## Results are averaged over the levels of: Intention, Symmetry, Weight
Attached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~WeightAttached)
```

```
## $emmeans
##  WeightAttached emmean    SE df lower.CL upper.CL
##  1                5.93 0.221 15     5.46     6.40
##  2                6.00 0.221 15     5.53     6.47
##  3                6.09 0.221 15     5.62     6.56
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE   df t.ratio p.value
##  1 - 2     -0.0671 0.0474 1899  -1.417  0.3324
##  1 - 3     -0.1587 0.0474 1899  -3.351  0.0024
##  2 - 3     -0.0916 0.0474 1899  -1.935  0.1293
##
## Results are averaged over the levels of: Intention, Symmetry, Distan
ceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
#Model with two-way interactions
model2 <- lme(DENTR ~ Intention + Symmetry + DistanceFromGrip + WeightA
ttached + Intention:Symmetry, data = dat, method = "REML", na.action =
"na.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')
```

```
##                        numDF  denDF   F-value p-value
## (Intercept)                1   1898  723.8455  <.0001
## Intention                  1   1898    2.3011  0.1294
## Symmetry                   1   1898    4.0781  0.0436
## DistanceFromGrip           1   1898    4.6902  0.0305
## WeightAttached             2   1898    5.6762  0.0035
## Intention:Symmetry         1   1898    6.2512  0.0125
```

```
#testing simple effects
simple.one <- lme(DENTR~Symmetry, subset=Intention=="Length", dat, meth
od = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Length"
##        AIC      BIC    logLik
##   2289.616 2309.075 -1140.808
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept)  Residual
## StdDev:    0.933408 0.7634961
##
## Fixed effects:  DENTR ~ Symmetry
##                         Value  Std.Error  DF   t-value p-value
## (Intercept)           6.15340 0.23593980 943 26.080383  0.0000
## SymmetrySymmetric    -0.11027 0.04928346 943 -2.237457  0.0255
##  Correlation:
##                      (Intr)
## SymmetrySymmetric   -0.104
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.37142912 -0.59327652  0.03465788  0.57542983  5.55283435
##
## Number of Observations: 960
## Number of Groups: 16
```

```
simple.two <- lme(DENTR~Symmetry, subset=Intention=="Weight", dat, meth
od = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: Intention == "Weight"
##        AIC      BIC    logLik
##   2396.922 2416.382 -1194.461
```

```
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:   0.9349702 0.808166
##
## Fixed effects:  DENTR ~ Symmetry
##                         Value  Std.Error  DF   t-value p-value
## (Intercept)        6.070569 0.23663533 943 25.653689       0
## SymmetrySymmetric -0.303343 0.05216689 943 -5.814866       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.11
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.59283313 -0.62031742 -0.01486464  0.58899204  3.36644079
##
## Number of Observations: 960
## Number of Groups: 16
```

```
#Creating models for laminarity
model <- lme(LAM ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.1918912
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120 120
##
## $MeanRel
##  [1] 0.9660958 0.9660958 0.9660958 0.9660958 0.9660958 0.9660958 0.9
660958
##  [8] 0.9660958 0.9660958 0.9660958 0.9660958 0.9660958 0.9660958 0.9
660958
## [15] 0.9660958 0.9660958
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(LAM ~ Intention + Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat, method = "REML", na.action = "na.omit", random = ~1|
```

```
ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                   numDF denDF   F-value p-value
## (Intercept)           1  1899 2098.1829  <.0001
## Intention             1  1899   24.4237  <.0001
## Symmetry              1  1899    0.7956  0.3725
## DistanceFromGrip      1  1899    0.0016  0.9680
## WeightAttached        2  1899    0.8582  0.4241

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##             R2m       R2c
## [1,] 0.01104508 0.2131567

#estimated marginal means
emmeans(model1,pairwise~Intention)

## $emmeans
##  Intention emmean   SE df lower.CL upper.CL
##  Length      72.4 1.51 15     69.2     75.6
##  Weight      75.0 1.51 15     71.8     78.2
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast        estimate    SE   df t.ratio p.value
##  Length - Weight     -2.6 0.526 1899  -4.942  <.0001
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip,
WeightAttached
## Degrees-of-freedom method: containment

#Model with two-way interactions
model2 <- lme(LAM ~ (Intention + Symmetry + DistanceFromGrip + WeightAt
tached)^2, data = dat, method = "REML", na.action = "na.omit", random =
~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                                   numDF denDF   F-value p-value
## (Intercept)                           1  1890 1636.7897  <.0001
```

```
## Intention                         1  1890    3.3523  0.0673
## Symmetry                          1  1890    0.6032  0.4375
## DistanceFromGrip                  1  1890    2.0686  0.1505
## WeightAttached                    2  1890    0.3851  0.6804
## Intention:Symmetry                1  1890    1.5908  0.2074
## Intention:DistanceFromGrip        1  1890    1.9440  0.1634
## Intention:WeightAttached          2  1890    1.4105  0.2443
## Symmetry:DistanceFromGrip         1  1890    0.5163  0.4725
## Symmetry:WeightAttached           2  1890    2.5538  0.0781
## DistanceFromGrip:WeightAttached   2  1890    0.4058  0.6665



#R code and results for experiment 2

#Retrieving data
path <- "D:/Exo/Dissertation/Participant data/Analysis2"
multmerge = function(path){
  filenames=list.files(path=path, full.names=TRUE)
  rbindlist(lapply(filenames, fread))
}
dat <- multmerge(path)
dat1 <- dat %>% filter(Intention == "Weight")
#converting variables to factors
dat1$ParticipantID <- factor(dat1$ParticipantID)
dat1$Symmetry <- factor(dat1$Symmetry)
dat1$DistanceFromGrip <- factor(dat1$DistanceFromGrip)
dat1$WeightAttached <- factor(dat1$WeightAttached)

#Creating models for perceived weight
model <- lme(PerceivedWeight ~ 1, data = dat1, method = "ML", na.action
= "na.omit", random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.2820601
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.959304 0.959304 0.959304 0.959304 0.959304 0.959304 0.959304
0.959304
##  [9] 0.959304 0.959304 0.959304 0.959304 0.959304 0.959304 0.959304
```

```
0.959304
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(PerceivedWeight ~ Symmetry + DistanceFromGrip + WeightAtt
ached, data = dat1, method = "REML", na.action = "na.omit", random = ~1
|ParticipantID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF  F-value p-value
## (Intercept)          1   940 76.45091  <.0001
## Symmetry             1   940 72.23520  <.0001
## DistanceFromGrip     1   940  7.13287  0.0077
## WeightAttached       2   940 96.47055  <.0001
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##            R2m       R2c
## [1,] 0.1553097 0.4530409
```

```
#estimated marginal means
emmeans(model1,pairwise~Symmetry)
```

```
## $emmeans
##  Symmetry   emmean   SE df lower.CL upper.CL
##  Asymmetric    171 13.7 15      142      200
##  Symmetric     131 13.7 15      102      161
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate   SE  df t.ratio p.value
##  Asymmetric - Symmetric     39.4 4.64 940   8.499  <.0001
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~DistanceFromGrip)
```

```
## $emmeans
##  DistanceFromGrip emmean   SE df lower.CL upper.CL
##  10                  145 13.7 15      116      174
##  20                  157 13.7 15      128      186
##
## Results are averaged over the levels of: Symmetry, WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate   SE  df t.ratio p.value
##  10 - 20     -12.4 4.64 940  -2.671  0.0077
##
## Results are averaged over the levels of: Symmetry, WeightAttached
## Degrees-of-freedom method: containment
```

```r
emmeans(model1,pairwise~WeightAttached)
```

```
## $emmeans
##  WeightAttached emmean   SE df lower.CL upper.CL
##  1                 111 13.8 15     81.4      140
##  2                 153 13.8 15    123.3      182
##  3                 190 13.8 15    160.3      219
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate   SE  df t.ratio p.value
##  1 - 2       -41.9 5.68 940  -7.380  <.0001
##  1 - 3       -78.9 5.68 940 -13.881  <.0001
##  2 - 3       -36.9 5.68 940  -6.501  <.0001
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```r
#Model with two-way interactions
model2 <- lme(PerceivedWeight ~ Symmetry + DistanceFromGrip + WeightAtt
ached + Symmetry:DistanceFromGrip, data = dat1, method = "REML", na.act
ion = "na.omit", random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')
```

```
##                             numDF denDF  F-value p-value
## (Intercept)                     1   939 65.13272  <.0001
## Symmetry                        1   939 12.56304   4e-04
```

```
## DistanceFromGrip              1   939 19.37856  <.0001
## WeightAttached                2   939 97.65290  <.0001
## Symmetry:DistanceFromGrip     1   939 12.52070   4e-04
```

```r
#testing simple effects
simple.one <- lme(PerceivedWeight~Symmetry, subset=DistanceFromGrip=="1
0", dat1, method = "REML", na.action = "na.omit", random = ~1|Participa
ntID)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat1
##   Subset: DistanceFromGrip == "10"
##        AIC      BIC    logLik
##   5383.778 5400.457 -2687.889
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    44.55798 63.40047
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                       Value Std.Error  DF   t-value p-value
## (Intercept)       156.54167 11.867468 463 13.190823   0e+00
## SymmetrySymmetric -23.10833  5.787645 463 -3.992701   1e-04
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.244
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.64331654 -0.36464263 -0.02793178  0.34518570 10.97631725
##
## Number of Observations: 480
## Number of Groups: 16
```

```r
simple.two <- lme(PerceivedWeight~Symmetry, subset=DistanceFromGrip=="2
0", dat1, method = "REML", na.action = "na.omit", random = ~1|Participa
ntID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat1
##   Subset: DistanceFromGrip == "20"
##        AIC      BIC    logLik
##   5729.335 5746.013 -2860.667
##
## Random effects:
```

```
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    59.67063 91.19719
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                       Value Std.Error  DF   t-value p-value
## (Intercept)       185.24167 16.037155 463 11.550781       0
## SymmetrySymmetric -55.73333  8.325126 463 -6.694593       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.26
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.14862951 -0.34726844 -0.03490292  0.24188709 12.20272071
##
## Number of Observations: 480
## Number of Groups: 16
```

```
model2 <- lme(PerceivedWeight ~ Symmetry + DistanceFromGrip + WeightAtt
ached + Symmetry:WeightAttached, data = dat1, method = "REML", na.actio
n = "na.omit", random = ~1|ParticipantID)
simple.one <- lme(PerceivedWeight~Symmetry, subset=WeightAttached=="1",
dat1, method = "REML", na.action = "na.omit", random = ~1|ParticipantID
)
summary(simple.one)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat1
##   Subset: WeightAttached == "1"
##        AIC      BIC    logLik
##   3100.788 3115.836 -1546.394
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    13.72541 29.62671
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                       Value Std.Error  DF   t-value p-value
## (Intercept)       121.01875  4.154524 303 29.129391       0
## SymmetrySymmetric -20.19375  3.312367 303 -6.096471       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.399
##
## Standardized Within-Group Residuals:
```

```
##          Min           Q1          Med           Q3          Max 
## -2.99062555 -0.42009021  0.02197813  0.33041191  4.76609917 
##
## Number of Observations: 320
## Number of Groups: 16
```

```
simple.two <- lme(PerceivedWeight~Symmetry, subset=WeightAttached=="2",
dat1, method = "REML", na.action = "na.omit", random = ~1|ParticipantID
)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat1 
##   Subset: WeightAttached == "2" 
##        AIC      BIC    logLik
##   3491.303 3506.351 -1741.651
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    51.58661 53.06158
##
## Fixed effects:  PerceivedWeight ~ Symmetry 
##                         Value Std.Error  DF   t-value p-value
## (Intercept)       171.75000 13.561738 303 12.664306       0
## SymmetrySymmetric -37.80625  5.932465 303 -6.372773       0
##  Correlation: 
##                   (Intr)
## SymmetrySymmetric -0.219
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max 
## -3.9000929 -0.3669798  0.0129205  0.3248877  7.6373275 
##
## Number of Observations: 320
## Number of Groups: 16
```

```
simple.three <- lme(PerceivedWeight~Symmetry, subset=WeightAttached=="3
", dat1, method = "REML", na.action = "na.omit", random = ~1|Participan
tID)
summary(simple.three)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat1 
##   Subset: WeightAttached == "3" 
##        AIC      BIC    logLik
##   3853.298 3868.346 -1922.649
##
```

```
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    93.35602 93.64408
##
## Fixed effects:  PerceivedWeight ~ Symmetry
##                        Value Std.Error  DF   t-value p-value
## (Intercept)       219.9062  24.48503 303  8.981252       0
## SymmetrySymmetric -60.2625  10.46973 303 -5.755881       0
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.214
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.49858289 -0.29388650 -0.02168379  0.22505429 10.27417716
##
## Number of Observations: 320
## Number of Groups: 16

#Analysis of MdRQA variables for EMG data in Experiment 2

#Retrieving data
path <- "D:/Exo/Dissertation/Participant data/EMGAnalysisMdRQA_Exp2/"
multmerge = function(path){
  filenames=list.files(path=path, full.names=TRUE)
  rbindlist(lapply(filenames, fread))
}
dat <- multmerge(path)
#converting variables to factors
dat$ParticipantID <- factor(dat$ParticipantID)
dat$Symmetry <- factor(dat$Symmetry)
dat$DistanceFromGrip <- factor(dat$DistanceFromGrip)
dat$WeightAttached <- factor(dat$WeightAttached)

#Creating models for determinance
model <- lme(DET ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.4240899
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
```

```
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9778677 0.9778677 0.9778677 0.9778677 0.9778677 0.9778677 0.9
778677
##  [8] 0.9778677 0.9778677 0.9778677 0.9778677 0.9778677 0.9778677 0.9
778677
## [15] 0.9778677 0.9778677
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(DET ~ Symmetry + DistanceFromGrip + WeightAttached, data
= dat, method = "REML", na.action = "na.omit", random = ~1|ParticipantI
D)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF denDF   F-value p-value
## (Intercept)          1   940 381300694  <.0001
## Symmetry             1   940        63  <.0001
## DistanceFromGrip     1   940         0  0.5226
## WeightAttached       2   940         3  0.0522

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##             R2m       R2c
## [1,] 0.03793334 0.4778365

#estimated marginal means
emmeans(model1,pairwise~Symmetry)

## $emmeans
##  Symmetry   emmean        SE df lower.CL upper.CL
##  Asymmetric 99.948 0.0049783 15   99.937   99.959
##  Symmetric  99.959 0.0049783 15   99.948   99.970
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate      SE  df t.ratio p.value
##  Asymmetric - Symmetric  -0.0109 0.00137 940  -7.958  <.0001
```

```
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~WeightAttached)

## $emmeans
##  WeightAttached emmean        SE df lower.CL upper.CL
##  1              99.952 0.0050254 15   99.942   99.963
##  2              99.952 0.0050254 15   99.941   99.963
##  3              99.956 0.0050254 15   99.945   99.967
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast  estimate      SE  df t.ratio p.value
##  1 - 2     0.000262 0.00168 940   0.156  0.9867
##  1 - 3    -0.003407 0.00168 940  -2.025  0.1067
##  2 - 3    -0.003669 0.00168 940  -2.181  0.0749
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es

#Model with two-way interactions
model2 <- lme(DET ~ (Symmetry + DistanceFromGrip + WeightAttached)^2, d
ata = dat, method = "REML", na.action = "na.omit", random = ~1|Particip
antID)
anova.lme(model2, type = 'marginal')

##                                 numDF denDF   F-value p-value
## (Intercept)                         1   935 349904395  <.0001
## Symmetry                            1   935         6  0.0131
## DistanceFromGrip                    1   935         1  0.4377
## WeightAttached                      2   935         0  0.6320
## Symmetry:DistanceFromGrip           1   935         0  0.4849
## Symmetry:WeightAttached             2   935         1  0.2514
## DistanceFromGrip:WeightAttached     2   935         2  0.2225

#Creating models for average diagonal line length
model <- lme(ADL ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.3171737
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9653621 0.9653621 0.9653621 0.9653621 0.9653621 0.9653621 0.9
653621
##  [8] 0.9653621 0.9653621 0.9653621 0.9653621 0.9653621 0.9653621 0.9
653621
## [15] 0.9653621 0.9653621
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(ADL ~ Symmetry + DistanceFromGrip + WeightAttached, data
= dat, method = "REML", na.action = "na.omit", random = ~1|ParticipantI
D)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF   F-value p-value
## (Intercept)          1   940 113.02823  <.0001
## Symmetry             1   940  38.68039  <.0001
## DistanceFromGrip     1   940   0.91373  0.3394
## WeightAttached       2   940   4.81950  0.0083
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##             R2m       R2c
## [1,] 0.03264716 0.3640741
```

```
#estimated marginal means
emmeans(model1,pairwise~Symmetry)
```

```
## $emmeans
##  Symmetry   emmean   SE df lower.CL upper.CL
##  Asymmetric   89.8 7.69 15     73.4      106
##  Symmetric   106.4 7.69 15     90.0      123
##
```

```
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate   SE  df t.ratio p.value
##  Asymmetric - Symmetric    -16.6 2.66 940  -6.219  <.0001
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment
```

```
emmeans(model1,pairwise~WeightAttached)
```

```
## $emmeans
##  WeightAttached emmean  SE df lower.CL upper.CL
##  1                94.9 7.8 15     78.3      112
##  2                95.4 7.8 15     78.8      112
##  3               103.9 7.8 15     87.3      121
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate   SE  df t.ratio p.value
##  1 - 2      -0.534 3.26 940  -0.164  0.9854
##  1 - 3      -9.031 3.26 940  -2.767  0.0159
##  2 - 3      -8.496 3.26 940  -2.603  0.0254
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
#Model with two-way interactions
model2 <- lme(ADL ~ (Symmetry + DistanceFromGrip + WeightAttached)^2, d
ata = dat, method = "REML", na.action = "na.omit", random = ~1|Particip
antID)
anova.lme(model2, type = 'marginal')
```

```
##                                   numDF denDF   F-value p-value
## (Intercept)                           1   935 114.96993  <.0001
## Symmetry                              1   935   4.18388  0.0411
## DistanceFromGrip                      1   935   1.75399  0.1857
## WeightAttached                        2   935   0.31885  0.7271
## Symmetry:DistanceFromGrip             1   935   0.80479  0.3699
```

```
## Symmetry:WeightAttached            2   935   0.51855  0.5956
## DistanceFromGrip:WeightAttached     2   935   2.60723  0.0743

#Creating models for maximum diagonal line length
model <- lme(MDL ~ 1, data = dat, method = "REML", na.action = "na.omit
", random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.6662632
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9917206 0.9917206 0.9917206 0.9917206 0.9917206 0.9917206 0.9
917206
##  [8] 0.9917206 0.9917206 0.9917206 0.9917206 0.9917206 0.9917206 0.9
917206
## [15] 0.9917206 0.9917206
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(MDL ~ Symmetry + DistanceFromGrip + WeightAttached, data
= dat, method = "REML", na.action = "na.omit", random = ~1|ParticipantI
D)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF denDF  F-value p-value
## (Intercept)          1   940 51.46755  <.0001
## Symmetry             1   940  0.51821  0.4718
## DistanceFromGrip     1   940  0.26163  0.6091
## WeightAttached       2   940  4.18484  0.0155

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##             R2m       R2c
## [1,] 0.00316242 0.6685334
```

```r
#estimated marginal means
emmeans(model1,pairwise~WeightAttached)

## $emmeans
##  WeightAttached emmean   SE df lower.CL upper.CL
##  1               10854 1497 15     7664    14045
##  2               11099 1497 15     7909    14290
##  3               10178 1497 15     6987    13369
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate  SE  df t.ratio p.value
##  1 - 2        -245 330 940  -0.743  0.7381
##  1 - 3         677 330 940   2.050  0.1011
##  2 - 3         922 330 940   2.793  0.0147
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es

#Model with two-way interactions
model2 <- lme(MDL ~ Symmetry + DistanceFromGrip + WeightAttached + Symm
etry:WeightAttached, data = dat, method = "REML", na.action = "na.omit"
, random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                         numDF denDF  F-value p-value
## (Intercept)                 1   938 51.29437  <.0001
## Symmetry                    1   938  0.01727  0.8955
## DistanceFromGrip            1   938  0.26286  0.6083
## WeightAttached              2   938  7.33742  0.0007
## Symmetry:WeightAttached     2   938  3.19628  0.0414

#testing simple effects
simple.one <- lme(MDL~Symmetry, subset=WeightAttached=="1", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)

## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "1"
##        AIC      BIC    logLik
##   6307.888 6322.937 -3149.944
##
```

```
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    5836.902 4384.267
##
## Fixed effects:  MDL ~ Symmetry
##                         Value Std.Error  DF  t-value p-value
## (Intercept)       10823.738 1499.8251 303 7.216667  0.0000
## SymmetrySymmetric    61.194  490.1759 303 0.124840  0.9007
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.163
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -2.2160987 -0.5568826 -0.1547368  0.3405482  7.5586585
##
## Number of Observations: 320
## Number of Groups: 16
```

```
simple.two <- lme(MDL~Symmetry, subset=WeightAttached=="2", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "2"
##        AIC      BIC    logLik
##   6292.673 6307.721 -3142.336
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    6357.822 4258.094
##
## Fixed effects:  MDL ~ Symmetry
##                        Value Std.Error  DF   t-value p-value
## (Intercept)       11381.56 1624.7121 303  7.005276  0.0000
## SymmetrySymmetric  -564.15  476.0694 303 -1.185016  0.2369
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.147
##
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -3.0352994 -0.5257202 -0.1367317  0.3768668  4.4010265
##
```

```
## Number of Observations: 320
## Number of Groups: 16

simple.three <- lme(MDL~Symmetry, subset=WeightAttached=="3", dat, meth
od = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.three)

## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "3"
##        AIC      BIC    logLik
##   6203.934 6218.982 -3097.967
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    5610.251 3700.977
##
## Fixed effects:  MDL ~ Symmetry
##                      Value Std.Error  DF  t-value p-value
## (Intercept)       9635.269 1432.7561 303 6.724989  0.0000
## SymmetrySymmetric 1084.919  413.7818 303 2.621958  0.0092
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.144
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.10617275 -0.48828633 -0.08447488  0.36853923  4.62941169
##
## Number of Observations: 320
## Number of Groups: 16

#Creating models for entropy
model <- lme(DENTR ~ 1, data = dat, method = "ML", na.action = "na.omit
", random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.6020196
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
```

```
## $MeanRel
##  [1] 0.9891021 0.9891021 0.9891021 0.9891021 0.9891021 0.9891021 0.9
891021
##  [8] 0.9891021 0.9891021 0.9891021 0.9891021 0.9891021 0.9891021 0.9
891021
## [15] 0.9891021 0.9891021
## 
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(DENTR ~ Symmetry + DistanceFromGrip + WeightAttached, dat
a = dat, method = "REML", na.action = "na.omit", random = ~1|Participan
tID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF  F-value p-value
## (Intercept)          1   940 738.1235  <.0001
## Symmetry             1   940   3.5142  0.0612
## DistanceFromGrip     1   940   0.0961  0.7566
## WeightAttached       2   940   6.0497  0.0025
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##               R2m       R2c
## [1,] 0.006178759 0.6228209
```

```
#estimated marginal means
emmeans(model1,pairwise~WeightAttached)
```

```
## $emmeans
##  WeightAttached emmean    SE df lower.CL upper.CL
##  1                8.66 0.318 15     7.98     9.34
##  2                8.68 0.318 15     8.00     9.36
##  3                8.44 0.318 15     7.76     9.12
## 
## Results are averaged over the levels of: Symmetry, DistanceFromGrip 
## Degrees-of-freedom method: containment 
## Confidence level used: 0.95 
## 
## $contrasts
##  contrast estimate     SE  df t.ratio p.value
##  1 - 2     -0.0193 0.0775 940  -0.249  0.9664
##  1 - 3      0.2233 0.0775 940   2.880  0.0113
##  2 - 3      0.2426 0.0775 940   3.129  0.0051
```

```
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es

#Model with two-way interactions
model2 <- lme(DENTR ~ (Symmetry + DistanceFromGrip + WeightAttached)^2,
data = dat, method = "REML", na.action = "na.omit", random = ~1|Partici
pantID)
anova.lme(model2, type = 'marginal')

##                                 numDF denDF  F-value p-value
## (Intercept)                         1   935 702.4225  <.0001
## Symmetry                            1   935   1.3978  0.2374
## DistanceFromGrip                    1   935   0.0024  0.9607
## WeightAttached                      2   935   1.4755  0.2292
## Symmetry:DistanceFromGrip           1   935   0.1336  0.7148
## Symmetry:WeightAttached             2   935   0.4725  0.6236
## DistanceFromGrip:WeightAttached     2   935   1.0126  0.3637

#Creating models for laminarity
model <- lme(LAM ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.4302252
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9784039 0.9784039 0.9784039 0.9784039 0.9784039 0.9784039 0.9
784039
##  [8] 0.9784039 0.9784039 0.9784039 0.9784039 0.9784039 0.9784039 0.9
784039
## [15] 0.9784039 0.9784039
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(LAM ~ Symmetry + DistanceFromGrip + WeightAttached, data
= dat, method = "REML", na.action = "na.omit", random = ~1|ParticipantI
```

```
D)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                    numDF denDF   F-value p-value
## (Intercept)            1   940 919392560  <.0001
## Symmetry               1   940        57  <.0001
## DistanceFromGrip       1   940         0  0.5266
## WeightAttached         2   940         3  0.0485

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##             R2m       R2c
## [1,] 0.03459247 0.4806115

#estimated marginal means
emmeans(model1,pairwise~Symmetry)

## $emmeans
##  Symmetry   emmean        SE df lower.CL upper.CL
##  Asymmetric 99.970 0.0032083 15   99.963   99.977
##  Symmetric  99.976 0.0032083 15   99.970   99.983
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate       SE  df t.ratio p.value
##  Asymmetric - Symmetric -0.00664 0.000877 940  -7.576  <.0001
##
## Results are averaged over the levels of: DistanceFromGrip, WeightAtt
ached
## Degrees-of-freedom method: containment

emmeans(model1,pairwise~WeightAttached)

## $emmeans
##  WeightAttached emmean        SE df lower.CL upper.CL
##  1              99.972 0.0032381 15   99.966   99.979
##  2              99.972 0.0032381 15   99.965   99.979
##  3              99.975 0.0032381 15   99.968   99.982
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
```

```
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast  estimate      SE  df t.ratio p.value
##  1 - 2     0.000301 0.00107 940   0.280  0.9576
##  1 - 3    -0.002127 0.00107 940  -1.980  0.1178
##  2 - 3    -0.002428 0.00107 940  -2.260  0.0621
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
#Model with two-way interactions
model2 <- lme(LAM ~ (Symmetry + DistanceFromGrip + WeightAttached)^2, d
ata = dat, method = "REML", na.action = "na.omit", random = ~1|Particip
antID)
anova.lme(model2, type = 'marginal')
```

```
##                                  numDF denDF   F-value p-value
## (Intercept)                          1   935 844992840  <.0001
## Symmetry                             1   935         5  0.0273
## DistanceFromGrip                     1   935         1  0.4628
## WeightAttached                       2   935         0  0.6108
## Symmetry:DistanceFromGrip            1   935         1  0.4538
## Symmetry:WeightAttached              2   935         1  0.2259
## DistanceFromGrip:WeightAttached      2   935         2  0.1636
```

```
#Analysis of MdRQA variables for kinematics data in Experiment 2

#Retrieving data
path <- "D:/Exo/Dissertation/Participant data/KinematicsAnalysisMdRQA_E
xp2/"
multmerge = function(path){
  filenames=list.files(path=path, full.names=TRUE)
  rbindlist(lapply(filenames, fread))
}
dat <- multmerge(path)
#converting variables to factors
dat$ParticipantID <- factor(dat$ParticipantID)
dat$Symmetry <- factor(dat$Symmetry)
dat$DistanceFromGrip <- factor(dat$DistanceFromGrip)
dat$WeightAttached <- factor(dat$WeightAttached)

#Creating models for determinance
```

```
model <- lme(DET ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.1356611
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.904005 0.904005 0.904005 0.904005 0.904005 0.904005 0.904005
0.904005
##  [9] 0.904005 0.904005 0.904005 0.904005 0.904005 0.904005 0.904005
0.904005
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(DET ~ Symmetry + DistanceFromGrip + WeightAttached, data
= dat, method = "REML", na.action = "na.omit", random = ~1|ParticipantI
D)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF denDF   F-value p-value
## (Intercept)          1   940 1221.7879  <.0001
## Symmetry             1   940    0.0561  0.8127
## DistanceFromGrip     1   940    0.8144  0.3670
## WeightAttached       2   940    2.9288  0.0539

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##              R2m       R2c
## [1,] 0.005965458 0.1497172

#Model with two-way interactions
model2 <- lme(DET ~ (Symmetry + DistanceFromGrip + WeightAttached)^2, d
ata = dat, method = "REML", na.action = "na.omit", random = ~1|Particip
antID)
anova.lme(model2, type = 'marginal')
```

```
##                                    numDF  denDF  F-value p-value
## (Intercept)                            1    935 916.1298  <.0001
## Symmetry                               1    935   0.0457  0.8308
## DistanceFromGrip                       1    935   0.0089  0.9250
## WeightAttached                         2    935   1.5253  0.2181
## Symmetry:DistanceFromGrip              1    935   0.1042  0.7469
## Symmetry:WeightAttached                2    935   3.4207  0.0331
## DistanceFromGrip:WeightAttached        2    935   0.4922  0.6115

#Creating models for average diagonal line length
model <- lme(ADL ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.03205699
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.6652294 0.6652294 0.6652294 0.6652294 0.6652294 0.6652294 0.6
652294
##  [8] 0.6652294 0.6652294 0.6652294 0.6652294 0.6652294 0.6652294 0.6
652294
## [15] 0.6652294 0.6652294
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(ADL ~ Symmetry + DistanceFromGrip + WeightAttached, data
= dat, method = "REML", na.action = "na.omit", random = ~1|ParticipantI
D)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF  denDF  F-value p-value
## (Intercept)          1    940 732.9761  <.0001
## Symmetry             1    940   0.6959  0.4044
## DistanceFromGrip     1    940   7.5053  0.0063
## WeightAttached       2    940   0.1661  0.8470

#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##                R2m        R2c
## [1,] 0.008510222 0.04360303

#estimated marginal means
emmeans(model1,pairwise~DistanceFromGrip)

## $emmeans
##  DistanceFromGrip emmean   SE df lower.CL upper.CL
##  10                 4.85 0.14 15     4.56     5.15
##  20                 5.23 0.14 15     4.93     5.53
##
## Results are averaged over the levels of: Symmetry, WeightAttached
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate    SE  df t.ratio p.value
##  10 - 20    -0.374 0.137 940  -2.740  0.0063
##
## Results are averaged over the levels of: Symmetry, WeightAttached
## Degrees-of-freedom method: containment

#Model with two-way interactions
model2 <- lme(ADL ~ (Symmetry + DistanceFromGrip + WeightAttached)^2, d
ata = dat, method = "REML", na.action = "na.omit", random = ~1|Particip
antID)
anova.lme(model2, type = 'marginal')

##                                 numDF denDF  F-value p-value
## (Intercept)                         1   935 434.0821  <.0001
## Symmetry                            1   935   0.6922  0.4056
## DistanceFromGrip                    1   935   0.0406  0.8404
## WeightAttached                      2   935   0.1752  0.8393
## Symmetry:DistanceFromGrip           1   935   0.0589  0.8083
## Symmetry:WeightAttached             2   935   1.5001  0.2236
## DistanceFromGrip:WeightAttached     2   935   1.6787  0.1872

#Creating models for maximum diagonal line length
model <- lme(MDL ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.3620689
##
## $Group
```

```
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9714726 0.9714726 0.9714726 0.9714726 0.9714726 0.9714726 0.9
714726
##  [8] 0.9714726 0.9714726 0.9714726 0.9714726 0.9714726 0.9714726 0.9
714726
## [15] 0.9714726 0.9714726
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(MDL ~ Symmetry + DistanceFromGrip + WeightAttached, data
= dat, method = "REML", na.action = "na.omit", random = ~1|ParticipantI
D)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF denDF   F-value p-value
## (Intercept)          1   940 104.86556  <.0001
## Symmetry             1   940   2.47938  0.1157
## DistanceFromGrip     1   940   1.24032  0.2657
## WeightAttached       2   940   7.18810  0.0008

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##             R2m       R2c
## [1,] 0.01154319 0.3882637

#estimated marginal means
emmeans(model1,pairwise~WeightAttached)

## $emmeans
##  WeightAttached emmean   SE df lower.CL upper.CL
##  1                68.7 6.83 15     54.2     83.3
##  2                62.5 6.83 15     47.9     77.0
##  3                58.8 6.83 15     44.3     73.4
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
```

```
##
## $contrasts
##  contrast estimate   SE  df t.ratio p.value
##  1 - 2        6.28 2.65 940   2.375  0.0466
##  1 - 3        9.92 2.65 940   3.747  0.0006
##  2 - 3        3.63 2.65 940   1.372  0.3559
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
#Model with two-way interactions
model2 <- lme(MDL ~ (Symmetry + DistanceFromGrip + WeightAttached)^2, d
ata = dat, method = "REML", na.action = "na.omit", random = ~1|Particip
antID)
anova.lme(model2, type = 'marginal')
```

```
##                                  numDF denDF   F-value p-value
## (Intercept)                          1   935 105.34044  <.0001
## Symmetry                             1   935   3.85100  0.0500
## DistanceFromGrip                     1   935   5.23131  0.0224
## WeightAttached                       2   935   6.11873  0.0023
## Symmetry:DistanceFromGrip            1   935   3.34167  0.0679
## Symmetry:WeightAttached              2   935   2.52852  0.0803
## DistanceFromGrip:WeightAttached      2   935   0.69927  0.4972
```

```
#Creating models for entropy
model <- lme(DENTR ~ 1, data = dat, method = "ML", na.action = "na.omit
", random = ~1|ParticipantID)
GmeanRel(model)
```

```
## $ICC
## [1] 0.6104934
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9894782 0.9894782 0.9894782 0.9894782 0.9894782 0.9894782 0.9
894782
##  [8] 0.9894782 0.9894782 0.9894782 0.9894782 0.9894782 0.9894782 0.9
894782
## [15] 0.9894782 0.9894782
```

```
##
## attr(,"class")
## [1] "gmeanrel"
```

```
model1 <- lme(DENTR ~ Symmetry + DistanceFromGrip + WeightAttached, dat
a = dat, method = "REML", na.action = "na.omit", random = ~1|Participan
tID)
#anova for fixed effects
anova.lme(model1, type = 'marginal')
```

```
##                  numDF denDF  F-value p-value
## (Intercept)          1   940 453.1654  <.0001
## Symmetry             1   940   3.6908  0.0550
## DistanceFromGrip     1   940   0.9676  0.3255
## WeightAttached       2   940   4.0127  0.0184
```

```
#R squared value for the fixed effects model
r.squaredGLMM(model1)
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.
```

```
##               R2m       R2c
## [1,] 0.004895421 0.6298655
```

```
#estimated marginal means
emmeans(model1,pairwise~WeightAttached)
```

```
## $emmeans
##  WeightAttached emmean    SE df lower.CL upper.CL
##  1                5.63 0.261 15     5.08     6.19
##  2                5.66 0.261 15     5.11     6.22
##  3                5.50 0.261 15     4.94     6.05
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate     SE  df t.ratio p.value
##  1 - 2     -0.0292 0.0626 940  -0.467  0.8870
##  1 - 3      0.1369 0.0626 940   2.187  0.0740
##  2 - 3      0.1661 0.0626 940   2.653  0.0221
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
#Model with two-way interactions
model2 <- lme(DENTR ~ (Symmetry + DistanceFromGrip + WeightAttached)^2,
data = dat, method = "REML", na.action = "na.omit", random = ~1|Partici
pantID)
anova.lme(model2, type = 'marginal')

##                                  numDF denDF  F-value p-value
## (Intercept)                          1   935 432.5618  <.0001
## Symmetry                             1   935   0.0098  0.9211
## DistanceFromGrip                     1   935   0.0140  0.9059
## WeightAttached                       2   935   1.6000  0.2024
## Symmetry:DistanceFromGrip            1   935   0.3405  0.5597
## Symmetry:WeightAttached              2   935   1.6544  0.1918
## DistanceFromGrip:WeightAttached      2   935   1.5734  0.2079

#Creating models for laminarity
model <- lme(LAM ~ 1, data = dat, method = "ML", na.action = "na.omit",
random = ~1|ParticipantID)
GmeanRel(model)

## $ICC
## [1] 0.2397009
##
## $Group
##  [1] 1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16
## Levels: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
##
## $GrpSize
##  [1] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
##
## $MeanRel
##  [1] 0.9497899 0.9497899 0.9497899 0.9497899 0.9497899 0.9497899 0.9
497899
##  [8] 0.9497899 0.9497899 0.9497899 0.9497899 0.9497899 0.9497899 0.9
497899
## [15] 0.9497899 0.9497899
##
## attr(,"class")
## [1] "gmeanrel"

model1 <- lme(LAM ~ Symmetry + DistanceFromGrip + WeightAttached, data
= dat, method = "REML", na.action = "na.omit", random = ~1|ParticipantI
D)
#anova for fixed effects
anova.lme(model1, type = 'marginal')

##                  numDF denDF   F-value p-value
## (Intercept)          1   940 2259.9832  <.0001
```

```
## Symmetry            1   940    0.0469  0.8285
## DistanceFromGrip    1   940    0.0226  0.8804
## WeightAttached      2   940    5.5481  0.0040

#R squared value for the fixed effects model
r.squaredGLMM(model1)

## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the
help page.

##              R2m       R2c
## [1,] 0.008613469 0.2602083

#estimated marginal means
emmeans(model1,pairwise~WeightAttached)

## $emmeans
##  WeightAttached emmean   SE df lower.CL upper.CL
##  1                73.6 1.49 15     70.4     76.8
##  2                71.9 1.49 15     68.7     75.1
##  3                71.2 1.49 15     68.0     74.3
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate    SE  df t.ratio p.value
##  1 - 2       1.724 0.754 940   2.288  0.0580
##  1 - 3       2.442 0.754 940   3.241  0.0035
##  2 - 3       0.718 0.754 940   0.953  0.6069
##
## Results are averaged over the levels of: Symmetry, DistanceFromGrip
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es

#Model with two-way interactions
model2 <- lme(LAM ~ Symmetry + DistanceFromGrip + WeightAttached + Symm
etry:WeightAttached, data = dat, method = "REML", na.action = "na.omit"
, random = ~1|ParticipantID)
anova.lme(model2, type = 'marginal')

##                         numDF denDF   F-value p-value
## (Intercept)                 1   938 2102.9493  <.0001
## Symmetry                    1   938    0.0639  0.8004
## DistanceFromGrip            1   938    0.0228  0.8799
## WeightAttached              2   938    7.1770  0.0008
## Symmetry:WeightAttached     2   938    5.1800  0.0058
```

```
#testing simple effects
simple.one <- lme(LAM~Symmetry, subset=WeightAttached=="1", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.one)

## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "1"
##       AIC      BIC    logLik
##   2358.03 2373.078 -1175.015
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    5.959968  9.08625
##
## Fixed effects:  LAM ~ Symmetry
##                      Value Std.Error  DF  t-value p-value
## (Intercept)       73.74693  1.654109 303 44.58409  0.0000
## SymmetrySymmetric -0.26831  1.015874 303 -0.26412  0.7919
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.307
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.38459959 -0.74055132  0.02955982  0.72333864  2.07138562
##
## Number of Observations: 320
## Number of Groups: 16

simple.two <- lme(LAM~Symmetry, subset=WeightAttached=="2", dat, method
= "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.two)

## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "2"
##        AIC     BIC    logLik
##   2381.082 2396.13 -1186.541
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    5.502333 9.469338
##
## Fixed effects:  LAM ~ Symmetry
##                      Value Std.Error  DF t-value p-value
```

```
## (Intercept)       73.12759  1.566096 303 46.6942  0.0000
## SymmetrySymmetric -2.47811  1.058704 303 -2.3407  0.0199
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.338
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.00032842 -0.63382108  0.05871435  0.69794870  2.11928530
##
## Number of Observations: 320
## Number of Groups: 16
```

```
simple.three <- lme(LAM~Symmetry, subset=WeightAttached=="3", dat, meth
od = "REML", na.action = "na.omit", random = ~1|ParticipantID)
summary(simple.three)
```

```
## Linear mixed-effects model fit by REML
##   Data: dat
##   Subset: WeightAttached == "3"
##        AIC      BIC    logLik
##   2391.357 2406.405 -1191.679
##
## Random effects:
##  Formula: ~1 | ParticipantID
##         (Intercept) Residual
## StdDev:    5.707206 9.615139
##
## Fixed effects:  LAM ~ Symmetry
##                      Value Std.Error  DF  t-value p-value
## (Intercept)       69.99713  1.616657 303 43.29745  0.0000
## SymmetrySymmetric  2.34645  1.075005 303  2.18273  0.0298
##  Correlation:
##                   (Intr)
## SymmetrySymmetric -0.332
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.09607822 -0.75078441  0.05185647  0.76590863  2.75293479
##
## Number of Observations: 320
## Number of Groups: 16
```

Appendix B

Sample Multidimensional Recurrence Plots for Experiment 2

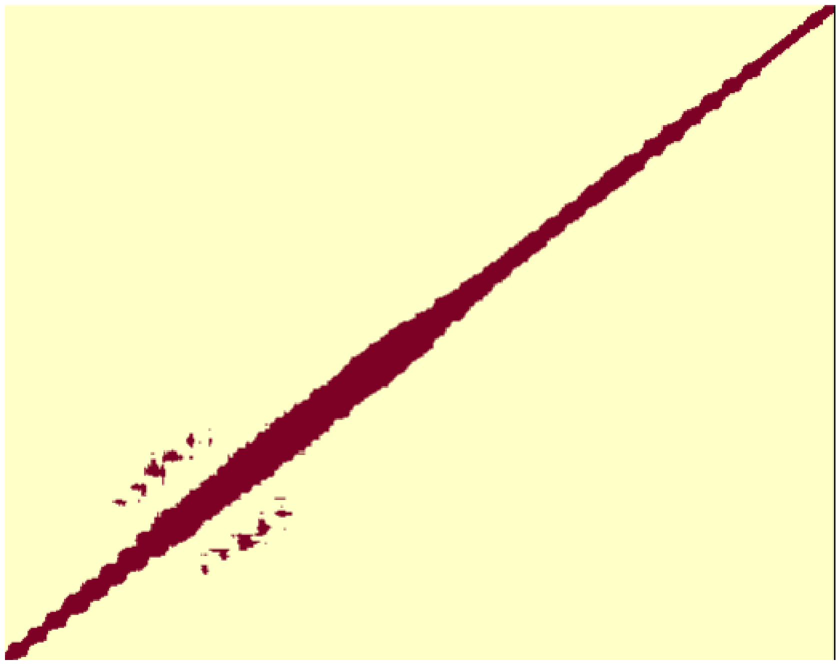


Figure B-1: MdRP for EMG data for a trial in experiment 2.

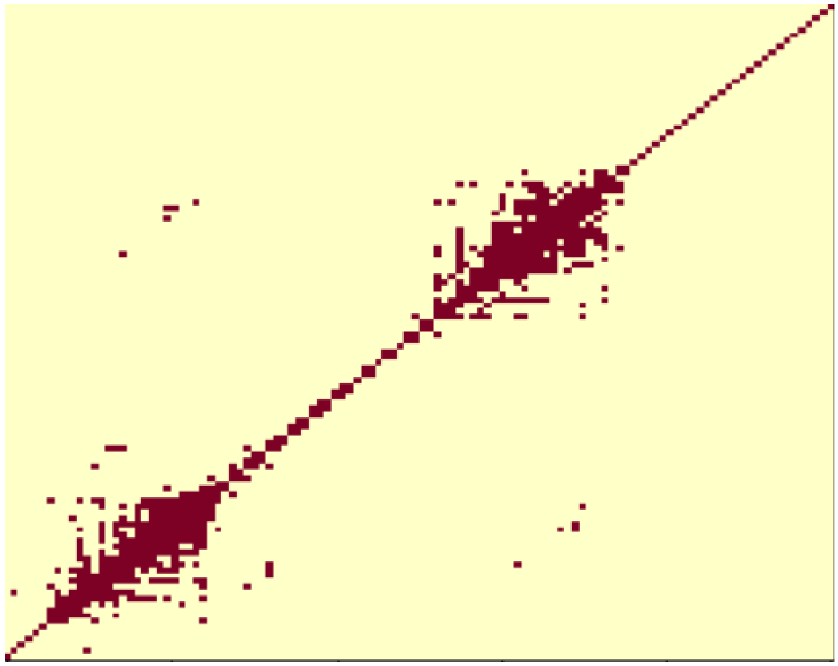


Figure B-2: MdRP for kinmeatics data for a trial in experiment 2.

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