REACHING KINEMATICS IN VR: EXPLORING THE INFLUENCE OF MOVEMENT DIRECTION, HAND DOMINANCE, HEMISPACE, AND ARM LENGTH

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A dissertation presented to the faculty of the School of Engineering and Applied Science, University of Virginia, in partial fulfillment of the requirements for the degree Doctor of Philosophy

May 2023

APPROVAL SHEET

This

Dissertation

is submitted in partial fulfillment of the requirements
for the degree of

Doctor of Philosophy

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For Hugh and Ruth Clark. You ignited my fascination with science, you taught me to be a life-long learner, and you were the best grandparents a guy could ask for. This dissertation is lovingly dedicated to you.

"If you are distressed by anything external, the pain is not due to the thing itself, but to your estimate of it; and this you have the power to revoke at any moment."

Marcus Aurelius

Abstract

As the concept of the metaverse fuels a growing interest in VR and other technologies that track users' arm movements [46], virtual hand reaching will continue to be a common way for users to select and manipulate the virtual objects presented in these displays. Kinematic analysis (KA) metrics quantify different useful properties of virtual hand reaches, including the speed, efficiency, and smoothness of these movements. These measures can provide valuable insights into users' movement behaviors to support emerging uses of VR technology in stroke rehabilitation (e.g., [144]) and motor skills training (e.g., [1]).

Past research suggests that some KA metrics can change when users perform reaching movements in different directions (i.e., *movement direction*). Furthermore, the effect of movement direction on these metrics may be different for reaches that occur on the same or opposite side of the user's body from the reaching arm (i.e., *interaction hemispace*), for reaches performed using the dominant or non-dominant arm (i.e., *hand dominance*), and for users with longer or shorter arms (i.e., *arm length*). However, no studies to-date have yet explored if and how all four of these factors may interact to influence the kinematic properties of virtual hand reaches. In the present work, we began to address this gap.

First, we performed an exploratory study that provided an initial look at how the first three factors (*movement direction*, *hand dominance*, and *interaction hemispace*) interact to influence the kinematic properties of virtual hand reaches (Chapter 2). A sample of 20 users performed virtual hand reaches in five cardinal directions (up, down, left, right, or away), on both sides of their bodies, using both their dominant and non-dominant hands. The results (1) revealed for the first time that these three factors interact to influence the kinematic properties of goal-directed reaches, and (2) provided a novel account of *how* each KA metric changes as a function of *movement direction* when users reach on either side of their body using either hand.

In the second study, we took a more detailed look at how KA metrics change as a function of movement direction for reaches performed on each side of the body using each hand (Chapter 3). Based on our results in the first study, we focused on reaches in 12 different directions that either involved moving inward (toward the body midline) or outward (away from the body midline). As in the first study, 20 users reached in each direction on both the left and right sides of their body, using both their dominant and

non-dominant hands. The results replicated our principal findings from Chapter 2 and provided a more fine-grained account of how the kinematic properties of virtual hand reaches change as a function of *movement direction* when users reach on either side of their body using either hand. In short, we found that the influence of *movement direction* on reaching kinematics is (1) vastly different for each KA metric and (2) depends heavily on both the hand used to perform movements and the side of the body on which movements occur.

In the third study, we examined if individual differences in *arm length* moderate the effects of movement direction on KA metrics, when users reach on each side of their body using each hand (Chapter 4). A sample of 40 users with a range of different arm lengths performed the same reaching task used in Chapter 3, and the length of each user's arms was measured using standard anthropometric procedures. We then examined (1) if the largest effects of movement direction on KA metrics that we observed in previous studies emerged differently for different individual users, and (2) if these effects were systematically different for users with shorter arms than for users with longer arms. The results indicated that there were meaningful differences between users concerning how they adapted the kinematic properties of their reaches to move in different directions, for reaches on each side of their body using each hand. However, in most cases, the effects of movement direction on KA metrics were not systematically different for users with shorter arms than for users with longer arms. This indicates that between-participant variation in the effects we examined was likely caused by individual differences in factor(s) other than arm length.

Together, these three studies provide the first empirical account of how *movement direction*, *hand dominance*, *interaction hemispace*, and individual differences in *arm length* interact to influence the kinematic properties of virtual hand reaches. Indeed, to our knowledge, this represents the first time that the joint influence of these four factors on movement kinematics has been explored for goal-directed reaches performed in any context, including for reaches performed to physical targets. Our findings have practical implications for work in several areas at the intersection of movement science and virtual reality, including laboratory research on motor control processes, predictive modeling of 3D reaching movements in VR, and the emerging use of VR-based kinematic analyses in applied contexts such as stroke rehabilitation, motor skills training, and usability assessment.

ACKNOWLEDGEMENTS

When thinking about how to thank the many folks who have helped me get to this point, I'm tempted to borrow the well-known Newton quote: "If I have seen further, it is by standing on the shoulders of giants". However, as I reflect on my professional journey so far, I feel like Newton's words fall a bit short. My giants have done much, much more than simply let me stand on their shoulders—they have taught me how to climb, guided me through some of the trickier pitches, and even carried me in difficult moments when I couldn't quite make it up myself. To the many giants who have helped me along the way, know that I am forever thankful for your support. As I reach this milestone in my professional journey, I'd like to take the opportunity to thank a few of you by name.

First, there are many people who have directly helped me complete a PhD. To my advisor, Dr. Sara Riggs: Thank you for your guidance, mentorship, and unwavering support. I am exceedingly thankful to have had the opportunity to learn from you and work with you over the past five years. To the members of my committee: Thank you for challenging me and pushing me to grow as a researcher. Your diverse perspectives and expertise have played a vital role in enhancing this work. Finally, to the many fellow students with whom I've been lucky enough to share this journey: Thank you for the friendship, perspective, and support that you've shared with me over the years. In particular, I would like to thank Kylie Gomes, Shannon Devlin, Katie Jurewicz, Courtney Rogers, Josh Biro, and Mohamad El Iskandarani for their help at several critical points in my PhD journey. Thank you also to Peiyu Zhang and Jeffrey Richbart for developing the reaching task software, without which this work would not have been possible.

There are also many other "giants" who played major parts in preparing me to pursue a PhD. Some were dedicated and passionate educators, including Elaine Gromak, Kathy Power, Bernadette Denison, Toni Tarsi, Paul Archer, Karla Dunnigan, Paul Davis, Nathan Stibrich, Christopher Cano, Amy Busquet, Mike Scicchitano, Juan Cruz, Peggy Martin, Rosalie Brennan, and Molly Biebel. Others were influential mentors, including Rodney King, Chris Hrabar, Kermit Davis, Daniel McConnell, and Mustapha Mouloua. You don't always get the recognition you deserve, but please know that I am thankful for the efforts you put into challenging me and helping me grow. Frankly, you all rock.

Finally, on the personal side of things, I owe immense thanks to a few special people who have been there for me over the years. To my parents, Dave and Marie Clark: A full thank you for everything you've done for me would be longer than this dissertation. You listened to me ramble for hours when I was a little "chatterbox", so I'll stick to the short version here: Thank you for always being in my corner. To my sisters, Sarah and Jeanine: Thank you for the many fun memories, and for always helping to make sure that I never take myself too seriously. Mom and Dad said we'd become friends when we grew up, and they were right. Finally, to Valerie Lewis: Thank you for being my "partner in crime" through the many ups and downs of the past seven years. This work and this part of my professional journey would not have been possible without your unwavering support. Love you, Valo.

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1 Introduction

1.1 Overview of the Research Gaps

Virtual hand interactions are a common way of enabling users to select and manipulate objects in modern virtual reality (VR) displays. In these interactions, users directly control the position, orientation, and grasping behaviors of virtual hands that are rendered in the VR environment by moving handheld controllers in the physical world [123,147]. One of the most common types of virtual hand interaction is *virtual hand reaching*, in which the user begins with their hand at a given starting point and reaches to select a target location somewhere in the virtual environment. Virtual hand reaches can be part of many different tasks that users regularly perform in VR, such as selecting options on a virtual menu, typing on a virtual keyboard, or picking up a virtual object. Interestingly, from a motor control perspective, virtual hand reaching can be characterized as the VR analog of a special class of arm movements known as *goal-directed reaching movements* [51,192]. Goal-directed reaching movements occur when a user needs to reach their hand from one spatial location to another as quickly and accurately as possible, often to point to or otherwise interact with an object at that location. Goal-directed reaches are a foundational building block of everyday human motor behavior, and they have therefore been studied extensively in the motor control literature. Given that virtual hand reaches are effectively goal-directed reaching movements performed in VR, this body of work and its associated tools may be useful for understanding users' behaviors during virtual hand reaching.

Kinematic analysis (KA) is one particularly useful tool that has been used for over 100 years [192] to study many different aspects of goal-directed reaching movements (e.g., [51,54,55,113]). KA techniques enable researchers to use motion tracking data describing the position of a user's hand over time while users perform goal-directed reaches to quantify different useful properties of those reaches (e.g., speed, efficiency, smoothness). Since modern VR systems can easily capture the motion tracking data needed to calculate KA metrics, these tools can be used to extract this same information for goal-directed reaching movements performed in VR (i.e., virtual hand reaches). This could be particularly useful in VR applications where there is value to be found in assessing different properties of a user's reaching movements, such as monitoring a patient's arm function recovery during VR-based stroke rehabilitation programs (e.g., [144,164]) or monitoring learners' progress during VR-based motor skills training (e.g., [1,153]).

Past research in movement science suggests that some kinematic properties of goal-directed reaching movements may change when users perform reaching movements in different directions (i.e., *movement direction*). Reaching kinematics may also change depending on whether a reach occurs on the same or opposite side of the user's body from the reaching arm (i.e., *interaction hemispace*), or whether the reach is performed using the dominant or non-dominant arm (i.e., *hand dominance*). The influence of these three factors on reaching kinematics may also vary across users, depending on the length of their arms (i.e., *arm length*). Changing these factors changes the underlying dynamics of the reaching task (in the case of movement direction, interaction hemispace, and arm length; e.g. [124,182]), or changes which of the two specialized hemisphere-limb systems performs the reaching movement (in the case of hand dominance; e.g., [162,163]). As users adapt their reaching behaviors to maximize performance subject to these different constraints (e.g., [51,178]), this can produce changes in the kinematic properties of their reaches. Past work examining goal-directed reaching movements in different contexts has provided some clues as to how *movement direction*, *hand dominance*, and *interaction hemispace* independently influence reaching movement kinematics, and some limited work has examined two-way interactions among these factors. However, to our knowledge, no studies to-date have yet thoroughly examined if and how all three of these factors may interact to influence the kinematic properties of goal-directed reaches. Furthermore, no work to date has explored if and how these three factors may influence reaching kinematics differently for users with different *arm lengths*. These gaps extend to goal-directed reaches performed in VR (i.e., virtual hand reaches), where the joint influence of these factors on reaching movement kinematics has also not yet been examined.

1.2 Why Address These Gaps?

Understanding how these factors interact to influence the kinematic properties of virtual hand reaches would bolster numerous research and design efforts at the intersection of human movement science and virtual reality. For work focused on improving the user experience of VR interfaces, this understanding would provide unique insights into how users behave while interacting with emerging consumer VR interfaces. This can be used to enhance predictive models of motor behavior and to better anticipate how users will move while interacting with VR interfaces. For laboratory work aimed at understanding human motor control processes (e.g., [51,54,55]), which has relied heavily on observing the kinematic properties of reaching movements performed in different contexts, this understanding would help to reveal if and how effects of movement direction on reaching kinematics that have been observed in past work may be different for reaches on either side of the body, using the dominant or non-dominant hand, and for reaches performed by different individual users. This can provide new observations to be accounted for by existing motor control theories.

Finally, and perhaps most critically, addressing these gaps would support work in several specific application areas where KA techniques show promise for answering questions about users' movement behaviors in VR. These include monitoring patients' progress during VR-based motor rehabilitation (e.g., [144,164]) and monitoring learners' progress during VR-based motor skills training (e.g., [1,153]). In both these contexts, the present work would provide a detailed quantitative account of how kinematic measures can be expected to change as a function of movement direction for reaches performed in either hemispace using either hand, and how the influence of these factors may be different for users with different arm lengths. This understanding can be used to interpret kinematic results obtained in these contexts more precisely. Specifically, by understanding (1) how healthy adults typically adapt the kinematic properties of their reaches to differences in movement direction for different combinations of hand, and hemispace, and (2) if and how these effects emerge differently for users with different arm lengths, researchers can better account for the effects of movement direction on reaching kinematics and factor them out if they are not of interest in a particular application.

In the sections below, we provide additional background information to further clarify the motivation for the present work. To begin, we provide a deeper background on kinematic analyses, including descriptions of the logic behind each of the KA metrics we examine in this work. We then introduce the four factors that we examine in the present work (i.e., *movement direction*, *hand dominance*, *interaction hemispace*, and *arm length*). For each factor, we summarize past work indicating that (1) users may adapt their movement behaviors in response to changes in each factor and (2) these adaptations can influence the kinematic properties of their reaching movements. We then review previous work that provides hints as to *how* the kinematic properties of virtual hand reaches may change depending on each of these factors. We conclude with a detailed description of our research goals for the present work.

1.3 Kinematic Analyses: Tools for Quantifying Movement Behavior

1.3.1 Overview of Kinematic Analysis

There are a broad range of different KA techniques, but the common feature of these analyses is that they use motion tracking data describing the position of the hand over time to quantify meaningful properties of a user's reaching movements. In general, KA techniques analyze movement behaviors by (1) converting hand position data into profiles that describe the velocity and acceleration of the hand over time, (2) smoothing these profiles using signal processing techniques, and (3) computing a range of different metrics designed to quantify different properties of these kinematic profiles [79,94]. The advantage of these measures over more general performance measures (e.g., error rate) is that they are not limited to quantifying users' overall performance on a reaching task—they can also provide a detailed look at how users behave *during* a movement. In short, KA measures can provide a detailed, quantitative account of how users plan and perform their reaching movements.

The use of KA to understand goal-directed reaching movements was pioneered by Woodworth [192]. In his seminal study, Woodworth examined the time course of hand position during reciprocal pointing movements between two target positions by asking users to hold a pencil and move between two targets positioned on either side of a rotating paper drum. By examining the paths traced out by the pencil, Woodworth was able to observe for the first time the presence of discrete corrective submovements near the end of users' reaching movements. This discovery paved the way for several subsequent models of speed-accuracy relations in goal-directed reaching [19,42,121], culminating most recently with the development of the multiple process model of goal-directed reaching [51,54,55]. In the years since, researchers have used kinematic analysis to answer a range of questions about goal-directed reaching movements in a broad variety of laboratory conditions. Naturally, the equipment used to record kinematic data has advanced considerably since Woodworth's seminal study, with optoelectronic motion capture systems coming to the forefront in recent decades. These systems have provided motion capture functionality for most kinematic studies, including those critical to the development of the multiple process model [51], optimal feedback control theory [45,178], and recent practical work using submovement decomposition approaches (e.g., [109,135]).

There are many different KA approaches in the literature, and these different approaches can yield a range of KA metrics that quantify different useful aspects of users' movement behaviors [169]. Here, we focus on a set of measures that quantify specific properties of users' movements which, based on the findings of past work, we suspect may change as users adapt their movement behaviors during virtual hand reaching. Specifically, there is evidence to suggest that the metrics *movement time* (MT; e.g., [75,112]), *peak velocity* (v_{peak}; e.g., [39,193]), *percent time to peak velocity* ($PTPV$; e.g., [142,143]), *percent time to the primary submovement endpoint* ($PTPSE$; e.g., [113]), and *primary submovement endpoint distance* (d_{PSE}; e.g., [39,113]) can each be influenced by at least one of these factors during virtual hand reaching or during goal-directed reaching performed under similar constraints. The final metric, $SPARC$, has received relatively less research attention [78]. However, this metric shows considerable promise as a useful measure of movement quality in several practical applications, especially in stroke rehabilitation [78,94]. Therefore, this metric was also examined in the present work. In the sections below, we introduce the general logic behind each of these measures and provide a brief conceptual overview of the mathematical procedures used to derive them. Detailed derivation procedures for each measure are provided in Chapter 2.

1.3.2 Measures of Movement Efficiency, Speed, and Profile Symmetry

The first measure, *movement time* (MT), indexes the amount of time it takes for a user to complete a movement. This provides a simple and intuitive measure of overall movement efficiency, based on the logic that more efficient movements will typically require less time to complete. We also examined *peak velocity* (v_{peak}), which indexes the maximum speed that the hand achieves during a movement. This is an intuitive measure of movement speed, following the logic that faster movements will tend to achieve a greater maximum speed.

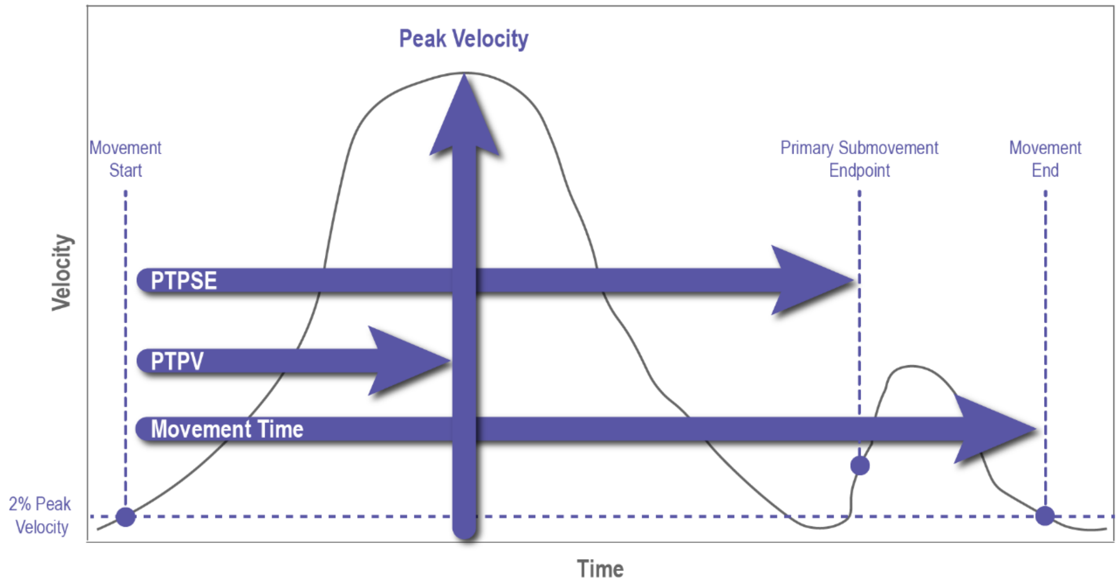
The third metric, *percent time to peak velocity* ($PTPV$), quantifies the general shape (i.e., skew) of the velocity profile for a reaching movement. As its name implies, this measure reflects the percentage of the total MT that has elapsed when v_{peak} occurs for a given movement. When this landmark occurs closer to the middle of a movement (i.e., near 50%), this indicates that the velocity profile for that movement is likely more symmetrical, with less time devoted to correcting the hand's position near the end of the movement. Conversely, when v_{peak} occurs earlier in the movement (smaller $PTPV$), this indicates that the velocity profile for that movement is likely less symmetrical, with more time devoted to correcting the hand's position in the latter portion of the movement. In this way, $PTPV$ provides a useful summary of how symmetric the velocity profile is for a given movement, which can be used to draw inferences about the strategies users employ to achieve their movements. See Figure 1.1 for a visual summary of the procedures used to calculate these two metrics.

1.3.3 Measures of Primary Submovement Endpoint Timing and Position

The next set of measures both quantify the properties of one particularly important kinematic landmark: the *primary submovement endpoint*. These measures are inspired by the multiple process model of goal-directed reaching [51,55], which posits that goal-directed reaching movements typically consist of two phases. First, in the *impulse control* phase, the user performs an initial high velocity submovement to bring the hand into the vicinity of the target. If the hand has not yet reached the target after this initial submovement, the user then performs one or more visually guided corrective submovements to close the remaining distance to the target (i.e., the *current control* phase). The primary submovement endpoint is the boundary between these two movement phases, and it can be identified for a given movement by using a specialized set of time and magnitude criteria to parse the velocity profile for that movement [36].

Once the primary submovement endpoint has been identified for a given movement, this information can be used to calculate two useful metrics. The first measure is the *percent time to the primary submovement endpoint* ($PTPSE$), which indexes the proportion of the movement that is spent in the first movement phase (i.e., impulse control). The second measure is *primary submovement distance* (d_{PSE}), which reflects the distance remaining between the user's hand and the target when the primary submovement endpoint occurs. Together with the other measures, these metrics can quantify several useful aspects of users' movement adaptations, such as the strategies they adopt when planning and executing their initial submovements (e.g., [113]) and the extent to which their movements rely on late corrective submovements. Figure 1.1 provides a conceptual summary of the procedures used to calculate these two metrics.

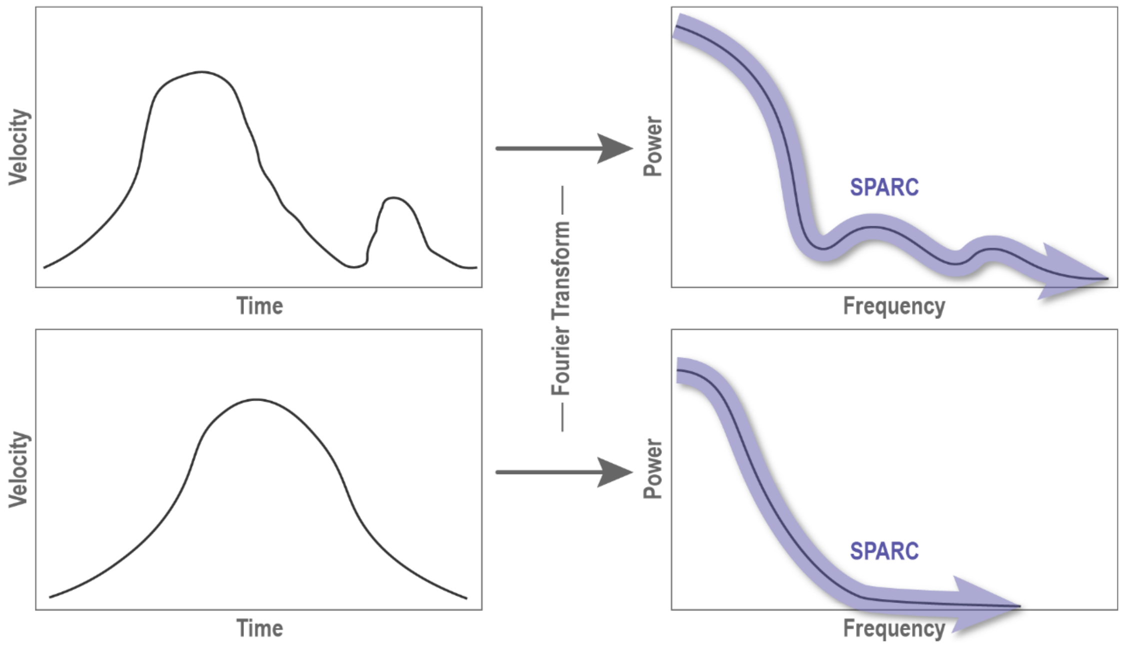
Figure 1.1: Visual summary of the procedures used to calculate movement time (MT), peak velocity (v_{peak}), percent time to peak velocity ($PTPV$), and percent time to the primary submovement endpoint ($PTPSE$).



1.3.4 $SPARC$: A Measure of Overall Movement Quality

The final measure, *spectral arc length* ($SPARC$), provides an index of the overall quality of a user's reaching movement [11,12,126]. This is based on the notion that optimally executed reaches will typically be performed in one smooth motion, while less optimal movements tend to involve more intermittent movement that is punctuated by multiple instances of acceleration, deceleration, and pauses as the hand temporarily comes to a stop during the reach. Smooth movements tend to contain less high-frequency oscillatory activity in their velocity profiles (i.e., fewer transient increases and decreases in speed), while more intermittent movements tend to contain more of this high-frequency activity. When the velocity profile for a movement is transformed into the frequency domain, this increased high-frequency activity produces more complex patterns in the Fourier magnitude spectrum, which represents the amount of power present at each frequency in the velocity profile. This is because smooth functions of time (in this case, the velocity profile for a smooth movement) also tend to be smooth functions of frequency (in this case, the Fourier magnitude spectrum for a smooth movement), while functions of time that are less smooth will tend to produce more complex frequency spectra that involve many undulations [11]. $SPARC$ quantifies the complexity of the Fourier magnitude spectrum, and therefore the smoothness of the associated movement, by calculating the arc length of this spectrum. Conceptually, this corresponds to the length of the line in the frequency-by-power plot, which becomes longer as the Fourier magnitude spectrum becomes more complex (Figure 1.2).

Figure 1.2: Visual summary of the procedure used to calculate spectral arc length ($SPARC$). As summarized by Balasubramanian and colleagues (2012), smoother functions of time (left) produce smoother function of frequency (right).



1.4 To What May Users Adapt During Virtual Hand Reaching?

As mentioned above, past work in human movement science suggests that users can adapt their movement behaviors in different ways when they complete virtual hand reaching movements with different task parameters. Although there are many different parameters that contribute to defining a virtual hand reaching task (e.g., target size, movement distance, etc.), we focus here on how users adapt to one property of virtual hand reaching tasks that has received comparatively less attention: the direction in which users' must move their hand to reach from their initial position and select a target object (*movement direction*). As users reach to targets involving different *movement directions*, we also examine if they may adapt their behaviors differently depending on (1) whether they are reaching using the dominant or non-dominant hand (*hand dominance*), and/or (2) whether the movement occurs on the same or opposite side of the user's body as the arm used to perform it (*interaction hemispace*). We also examine if these effects may emerge differently for different users depending on the length of their arms (*arm length*).

In the sections below, we introduce each of these four factors of interest (i.e., *movement direction*, *hand dominance*, *interaction hemispace*, and *arm length*). We then discuss why there is reason to suspect that users might adapt their movement behaviors during virtual hand interactions when faced with differences in each of these factors. For each task property, we introduce the ways in which differences in that property (e.g., requiring users to move in different *movement directions*) can influence various constraints involved in planning and executing the 3D reaching movements that comprise virtual hand interactions. We then summarize previous work indicating that (1) users can adapt their movement behaviors in response to changes in those constraints, and (2) these adaptations can produce measurable changes in the kinematic properties of users' reaching movements.

1.4.1 Task Property: Movement Direction

During virtual hand interactions, users often need to move their hands in different directions to select targets at different locations in 3D space. Based on past work in movement science, there are several reasons to suspect that users may adapt their movement behaviors based on the direction in which they need to move to select a target. Many of these relate to the fact that movements performed in different directions can differ in the extent to which they recruit each segment of the arm [120,124,167,170,182]. As the patterns of limb segment involvement change for movements in different directions, this also changes several dynamic forces and constraints to which users are known to adapt when planning and executing reaching movements. These include direction-dependent changes in the inertial resistance of the arm to movement [59,72,176], execution-related neuromotor noise [18,52,99,149], the time and effort coasts of making different types of trajectory errors [21,25,50,113,157], and the gravitational torques [65,66,188,195] and interaction torques between adjacent limb segments [73,84,160,196] that act on each segment of the limb. We introduce each of these factors in more detail below.

1.4.1.1 Inertial Anisotropy

First, direction-dependent differences in the degree of involvement of each limb segment can produce corresponding direction-dependent changes in the inertial resistance of the limb to acceleration. For example, a movement that can be completed using just rotation about the elbow only requires the participant to accelerate the mass of the hand and lower arm, while a movement that involves both the lower and upper arms must accelerate the mass of the hand and both the upper and lower arm. As a result, the inertial resistance of the limb can vary as a function of movement direction, in a phenomenon known as *inertial anisotropy* (i.e., indicating that limb inertia is anisotropic in three-dimensional space). Past work in the movement science literature suggests that for 2D reaching movements in the horizontal plane, limb inertia as a function of movement direction in 2D space can be summarized by an ellipse. Namely, in this context, inertial resistance is largest for movement directions that are aligned with the initial orientation of the lower arm (corresponding to movements that require the user to engage both the lower and upper arm), smallest for movement directions perpendicular to the lower arm (corresponding to movements involving engagement of only the lower arm) and assumes intermediate values for other movement directions [72,83].

There is evidence that users can adapt their movement behaviors to account for these direction-dependent differences in limb inertia and that these adaptations can influence the kinematic properties of users' reaching movements. For example, Gordon and colleagues [72] found that for 2D reaches that involved the same movement distance but were performed in different directions in the horizontal plane, the speed and efficiency of those movements varied predictably as a function of estimated limb inertia. As inertial resistance to movement increased, users tended to exhibit smaller peak velocity and peak acceleration and longer movement times. Further analysis revealed that the velocity profiles for users' reaching movements tended to scale as a function of limb inertia, such that movements involving greater inertia yielded longer velocity profiles with more prominent peaks. This pattern generalized to movements involving different initial arm postures and speeds, and it emerged regardless of whether targets were presented directly in the horizontal plane workspace or on a vertical computer monitor. Similar findings have been observed for 2D reciprocal pointing tasks in the horizontal plane [59], and for discrete 2D reaches performed using a computer mouse [176]. Although this work focused on 2D reaching movements, we expect that direction-dependent differences in limb inertia may also influence the 3D reaching movements that comprise virtual hand interactions. However, for 3D movements, the relationship between movement direction and limb inertia may be much more complex. This is because in 3D reaches a much broader range of initial limb configurations can be used to complete any given movement, and both the initial movement directions and the associated direction-dependent differences in limb inertia are free to vary in three dimensions instead of two.

1.4.1.2 Interaction Torques

Second, movements involving different patterns of limb segment recruitment can be subject to different patterns of intersegmental *interaction torques*, which occur when the movement of one limb segment exerts a force on an adjacent segment. For example, moving the upper arm can exert an interaction torque on the lower arm via the connection at the elbow [161]. The magnitude of interaction torques can vary over time based on the velocity and acceleration of each segment and the physical configuration of the limb, and during reaching movements these torques can sometimes exceed those produced by muscle action applied to the limb segments [67,73,160]. These forces can become more complicated for unconstrained 3D movements, where joints such as the shoulder can exploit multiple degrees of freedom. For these cases, interaction torques can also occur *within* limb segments. This occurs when movement in one degree of freedom for a joint also induces movement along the other degrees of freedom for that joint [186].

Past work in movement science suggests that the human motor system can organize movement trajectories to compensate for interaction torques [73,84,160,196]. The motor system can also take advantage of interaction torques by incorporating them into movement plans, thereby reducing the amount of muscular torque necessary to perform a given movement [43,49,161,171,186]. Critically, there is evidence that as users adapt their movement behaviors to perform movements involving different patterns of interaction torques, these adaptations can manifest as changes in several kinematic properties of those movements [161,179,186,194]. Together, this body of work suggests that direction-dependent differences in limb segment recruitment can produce movements involving different patterns of inter- and intra-segmental interaction torques, and that when the motor system compensates for these torques or incorporates them into movement this can produce measurable changes in the kinematic properties of users' arm movements.

1.4.1.3 Execution-Related Neuromotor Noise

Third, when movements engage different limb segments to varying extents, these movements also vary in the extent to which they engage different muscles. Specifically, when 3D reaching movements have been examined at the level of individual muscles using EMG, movements in different directions have been found to involve different patterns of activation in the muscles of the shoulder, arm, and chest [124,182]. In parallel, studies of noise in the human motor system have demonstrated that some muscles can exhibit greater variability in their force output than others. Namely, muscles that can produce larger forces also tend to produce more variable forces [56,90,168]. The resulting differences in force output variability from the muscles that contribute to a movement can cause users' reaching movements to become more variable (i.e., less consistent), in a phenomenon known as *execution-related neuromotor noise* [4,5,18]. The result is that participants can reach targets less consistently with their initial reaching movements, and the endpoints of their initial attempts to reach a target can become more spread out in space.

Critically, there is evidence that as users' reaching movements become more variable, users tend to adopt more conservative movement strategies to maintain acceptable reaching performance despite this variability [51,52,55]. Furthermore, there is evidence that these strategic adjustments can produce measurable changes in the kinematic properties of users' reaching movements [52,99,149]. Together, this body of work suggests that direction-dependent differences in limb segment recruitment may coincide with direction-dependent differences in the variability of arm movements, and adaptations to account for these changes in movement variability may produce direction-dependent differences in the kinematic properties of reaching movements.

1.4.1.4 Gravitational Torques

Fourth, during 3D reaching movements, the motor system must also account for gravitational torques due to the downward force of gravity on each limb segment. The influence of gravity on reaching movements can vary as a function of movement direction in 3D space, as different limb segments are required to move with or against the force of gravity for movements in different directions (e.g., when moving up vs. down). There is evidence that the human motor system can account for these different patterns of gravitational forces when planning and executing reaching movements, and that adapting movements in this way can help to minimize the muscular effort required to perform a given movement [65,188]. These types of direction-dependent adaptations to gravitational torques have been found to influence several kinematic properties of reaching movements, including time to peak velocity [66,195].

Direction-dependent differences in gravitational torques also change the effort costs associated with different types of errors in reaching performance. For example, the effort costs associated with overshooting a target with the hand (i.e., the effort involved in performing a corrective movement to reach the target successfully after overshooting the target) are higher for downward movements than for upward movements. This is because for downward movements, overshooting the target requires participants to move back upwards against gravity to reach the target, while for upward movements the same error can be corrected by moving downwards with the aid of gravity. There is evidence that participants can adapt their movement strategies to account for these gravity-dependent changes in the effort costs associated with different types of movement errors, and these adaptations can manifest as measurable changes in the kinematic properties of users' reaching movements [50,113,139]. These results are consistent with more recent work modeling arm movements using the principles of optimal control [177,178], which suggests that the motor system may plan and execute movements by optimizing a cost function that is tailored to maximize task performance while minimizing muscle effort [65]. Together, this body of work suggests that participants can adapt their movement behaviors to account for direction-dependent differences in the influence of gravitational forces, and these adaptations can coincide with measurable direction-dependent differences in the kinematic properties of reaching movements.

1.4.1.5 Direction-Dependent Task Performance and Effort Costs

As discussed at several points above, there is considerable evidence to suggest that users can adapt their movement behaviors to maximize task performance while minimizing the time and effort costs associated with achieving that performance (e.g., [45,51,113,178]). For example, studies examining reaching movements to physical targets have revealed that when it takes more time and effort to correct an overshoot error (i.e., moving past the target with the initial reach) than an undershoot error (i.e., ending the initial reach short of the target), users tend to *undershoot* the target more frequently with their primary submovements [21,25,50,113,157]. However, when overshooting the target is preferable to undershooting in terms of the time and effort required to perform corrections, users instead tend to *overshoot* the target more frequently with their initial submovements [139]. This pattern has been taken to reflect a general bias toward avoiding “worst case” outcomes in the planning and execution of reaching movements.

In the past, these strategic adaptations have typically been observed when comparing the kinematic properties of downward and upward movements, since corrections following an overshoot when moving downward must be performed against gravity, while similar corrections when moving upward are performed with the aid of gravity. In these conditions, subjects tend to undershoot targets more severely with their initial reaches when moving downward compared to when moving upward, reflecting a strategic adaptation to minimize the chance of needing to perform more effortful corrections against gravity [113]. Naturally, we would expect these adaptations to the time and effort contingencies introduced by gravity to generalize to 3D reaches performed in VR. However, for unconstrained 3D movements, there is also reason to suspect that the biomechanical factors described above (i.e., inertial anisotropy of the limb, interaction torques) may also contribute to the effort costs associated with different patterns of movement behavior. This could lead subjects to adopt unique time- and effort-minimizing movement strategies that have not yet been observed in the context of reaching movements that primarily involve moving within one 2D plane.

1.4.1.6 Direction-Dependent Reliability of Visual and Proprioceptive Sensory Information

In addition to the biomechanical and strategic constraints discussed above, reaching movements performed in VR are also subject to unique perceptual constraints that may not be present during similar movements performed in the real world. Namely, past work has revealed that participants’ depth perception can be less accurate in VR displays than in real-world environments, such that users tend to underestimate the depth of virtual objects that are positioned "behind" the screen, as is the case with HMD-based VR displays [156,185]. This reduced accuracy when localizing virtual targets has been attributed to a range of technological limitations of VR displays, including the limited field of view, limited availability of nonpictorial depth cues, and the vergence-accommodation conflict, among other factors [156]. Although many of these problems have been at least partially addressed in modern HMDs, lingering depth perception inaccuracy could still produce uncertainty when localizing the position of the hand and target in 3D space, which is a critical part of planning and executing reaching movements [140,178].

Furthermore, when users are uncertain about the location of a target, there is evidence that they can adapt their movement behaviors to maximize performance despite that uncertainty. These adaptations can include planning movements to minimize the effort involved in adjusting to reach the actual target location when it becomes apparent later in the movement [35,76,172,191]. They can also involve performing larger and more frequent corrective movements when an initial movement that was planned using inaccurate depth information fails to reach the target [14,114].

Examining these two sets of findings together, consider that during virtual hand reaches in VR, movements in different directions may differ in the extent to which participants must rely on depth perception to accurately localize the target. For example, movements performed away from the body to targets positioned at a different depth than the starting position may require participants to rely more heavily on depth perception to localize the target, while movements to targets positioned at the same depth as the starting position (e.g., to the left or right in the vertical plane) may be less dependent on accurate depth perception. As discussed above, users can sometimes adapt their reaching behaviors when faced with perceptual uncertainty, so these direction-dependent differences in the importance of depth estimation for localizing targets may produce corresponding direction-dependent changes in the kinematic properties of users' reaching movements. This is consistent with recent findings concerning the effects of stereo display deficiencies on 3D pointing movements, which revealed that movements to virtual targets positioned at varying depths exhibit performance decrements on kinematic measures that do not occur when movements are instead performed to identically positioned physical targets [14,114]. In short, this suggests that stereo display deficiencies may be yet another driver of direction-dependent behavioral adaptations during virtual hand pointing movements in VR.

1.4.2 Moderating Factor: Interaction Hemispace

Past work in movement science suggests that users may adapt their behaviors to changes in *movement direction* differently depending on at least two other properties of 3D reaching tasks. The first of these potential moderating factors is *interaction hemispace*, which refers to the side of the body on which a movement occurs relative to the arm performing the movement. If a movement occurs on the same side of the body as the moving arm (e.g., on the right side for a movement using the right arm), then it is said to occur in the ipsilateral hemispace. Conversely, if a movement occurs on the opposite side of the body from moving hand (e.g., on the left side for a movement using the right arm), then it occurs in the contralateral hemispace. Together with *movement direction*, this factor may influence users' reaching behaviors by changing the biomechanical constraints governing the planning and execution of reaching movements. Naturally, there is evidence that these changes can manifest in the kinematic properties of users' movements (e.g., [26,97]).

First, consider that patterns of limb segment recruitment can vary not just as a function of movement direction [120,167,182] but also depending on the hemispace in which a given movement occurs [154]. For example, imagine that a user is asked to begin with their right arm at a specified starting position and reach to select a target located directly to the left of that starting position. If this movement were to occur in the hemispace *ipsilateral* to the reaching arm, then it would involve the participant beginning with their arm on the right side of their body and moving their hand inward toward their body midline to reach the target. This movement could be completed by rotating the forearm about the elbow and performing a small horizontal shoulder adduction. If this movement were instead to occur in the hemispace *contralateral* to the reaching arm, then the participant would need to begin the task with their arm already reaching across their body. In this case, moving the same distance to the left of the starting position to select the same target would require the participant to reach even farther across their body (i.e., greater horizontal shoulder adduction combined with elbow extension). In this way, moving the same distance in the same direction can require different patterns of limb segment recruitment depending on the *hemispace* in which the movement occurs.

As discussed above in the context of *movement direction*, different patterns of limb segment engagement can produce differences in several dynamic properties that are known to influence the planning and execution of reaching movements, including the inertial resistance of the limb (e.g., [72]), interaction torques (e.g., [161]), and execution-related motor noise (e.g., [18]). It therefore stands to reason that if *movement direction* and *interaction hemispace* can interact to influence patterns of limb segment recruitment during reaching movements, then these dynamic properties and their associated influences on users' movement behaviors may also vary as a function of both *movement direction* and *interaction hemispace*. Consistent with this notion, studies examining the source of hemispace-dependent differences in the kinematic properties of reaching movements have generally found that kinematic differences between movements performed in the contralateral and ipsilateral hemispaces likely emerge from hemispace-dependent differences in these types of biomechanical constraints [26,27,30,100,101,154].

1.4.3 Moderating Factor: Hand Dominance

The second potential moderating factor that we consider here is *hand dominance*. This factor reflects the fact that virtual hand reaches can typically be performed using either the dominant or non-dominant arm. To understand how *hand dominance* may influence how users adapt their movement behaviors in VR, it is useful to understand precisely how movements performed using the dominant and non-dominant limbs are different. Recent work to this end has revealed that the dominant and non-dominant arms may be specialized to take advantage of different control processes [162,163]. Specifically, this body of work suggests that the dominant arm and its associated cerebral hemisphere are specialized for predictive control processes, which coordinate muscle activation with dynamic properties of the limb such as interaction torques to produce straight, smooth, and efficient movement trajectories [163]. This allows the dominant limb to produce movements that are more energy efficient and follow straighter trajectory paths than movements with the non-dominant limb. Conversely, the non-dominant arm and its associated cerebral hemisphere are specialized for impedance-based control, which involves modulating the effective stiffness of the arm during movement. Movements with the non-dominant arm tend to be less energy efficient than movements performed with the dominant arm [9], but they are more robust to the influence of unexpected disruptions from external sources (e.g., mechanical perturbations) and internal sources (e.g., motor noise; [163]). This account posits that while each arm/hemisphere system is specialized for a particular type of control, both hemispheres contribute to the movements of each arm. However, movements with the arm contralateral to a given hemisphere are purportedly influenced more strongly by the control scheme for which that hemisphere is specialized [162,163,194].

There are at least two ways in which the hand-specific specializations for predictive or impedance control may lead users to adapt differently to changes in *movement direction* when using the dominant vs. non-dominant hand. First, recall that the influence of gravity on reaching movements can vary as a function of movement direction, as different limb segments are required to move with or against the force of gravity for movements in different directions. Research on handedness has revealed that the dominant limb can be more effective than the non-dominant limb at taking advantage of gravitational torques when planning and executing reaching movements [146]. This may be due to the dominant limb's greater reliance on predictive control mechanisms that can account for these torques during movement planning. This difference in how the two hands account for gravitational torques has been proposed to influence several kinematic properties of goal-directed reaching movements [65,146,165]. Together, this body of work suggests that users may adapt differently to direction-dependent gravitational torques when performing movements using the dominant and non-dominant limbs, and these differential adaptations can be reflected in the kinematic properties of users' movements.

Second, recall that *movement direction* and *interaction hemispace* can jointly influence the pattern of interaction torques involved in performing a given reaching movement [120,154,167,182]. The dominant arm is generally more effective than the non-dominant arm at integrating these interaction torques into movement plans [162,163], and this interlimb difference has been found to influence several kinematic properties of reaching movements [9,161,179]. Given these findings, it stands to reason that the kinematic properties of movements performed in a given direction and hemispace may be different for movements performed using the dominant and non-dominant limbs (e.g., [97], study 2). In short, *movement direction*, *interaction hemispace*, and *hand dominance* may all interact to influence the kinematic properties of 3D reaching movements.

1.4.4 Moderating Factor: Individual Differences in Arm Length

The final potential moderating factor that we consider here is arm length, which reflects the fact that some individual users naturally will have longer arms than others. Notably, to our knowledge, no work to-date has yet examined if and how these individual differences in arm length influence reaching movement kinematics in either the real world or VR (see section 1.5.4). However, there is significant reason to think that the influence of movement direction on reaching kinematics may be different for users with different arm lengths. Specifically, the length of a user's limb segments influences the inertial properties of their limbs, since the moment of inertia for each limb segment changes as the length of that segment increases. As described in detail above (section

1.4.1.1), there is evidence that users can adapt their reaching behaviors to account for differences in limb inertia and that these adaptations can influence the kinematic properties of goal-directed reaches (e.g., [59,72]). In turn, differences in the inertial properties of users' limbs can also influence other factors to which users have been found to adapt their reaching behaviors. These include the magnitude of the interaction torques between adjacent limb segments (e.g., [73,84,160,196]; section 1.4.1.2), the magnitude of the muscular forces required to perform the movement and the associated execution-related neuromotor noise (e.g., [4,5,18]; section 1.4.1.3), and the effort costs associated with different movement strategies (e.g., [51,113]; section 1.4.1.5). As such, when users adapt their reaching behaviors to maximize performance (i.e., speed and accuracy) and minimize the effort required to perform a given movement [51,178], there is considerable reason to suspect that users with different arm lengths may adapt their reaching behaviors differently, such that the influence of movement direction on reaching kinematics may be different for users with different arm lengths.

1.5 Related Work

Research to-date has shed some light on how the kinematic properties of users' movements may change when they adapt their movement behaviors to differences in *movement direction*, *hand dominance*, and *interaction hemispace* during virtual hand reaching, and how these effects may emerge differently for users with different *arm lengths*. In the sections below, we summarize the relevant work examining the influence of each of these four factors on reaching kinematics. For each factor, we first cover any work that has examined how users adapt their behaviors to differences in that factor during virtual hand reaching (i.e., studies examining 3D reaching movements performed in VR). We then broaden our scope to consider past work that examined movements performed in other task contexts, including 3D reaching to physical targets, 2D reaches constrained to the horizontal plane, reciprocal pointing between two adjacent targets, uncorrected 3D reaching movements, and reaching movements performed without visual feedback of the hand. Because the constraints of these other tasks differ from those involved in virtual hand reaching, we can be less confident that patterns of adaptation observed during these tasks will also emerge during virtual hand reaching. However, this secondary body of work can nonetheless supplement the limited work on adaptations during virtual hand reaching and provide some hints as to the patterns of differences in the kinematic properties of virtual hand reaches that we might expect to observe in our present work.

1.5.1 Effects of Movement Direction

1.5.1.1 In Virtual Hand Reaching Tasks

Research to-date provides some initial clues as to how the kinematic properties of virtual hand reaches may change when users reach in different movement directions. These studies have typically been designed to address other research questions, but in the process they have provided some kinematic results that shed some light on this question. For example, in a study examining strategic biases in reaching movements performed in VR, Clark and Riggs [39] had users perform discrete 3D reaching movements from a central starting location to select targets positioned in six different directions in a VR environment. The task required users to reach primarily along the horizontal axis (directly to the left or right of the starting position), vertical axis (directly up or down), or depth axis (directly toward or away from the user). All participants were right-handed and used their dominant right hand to select each target. In this context, peak velocity (v_{peak}) was significantly larger for downward movements and movements to the right than for all the other movement directions, suggesting that movements in these directions achieved a higher speed than movements in the other directions. However, this change in peak speed did not translate into an observably large difference in overall movement efficiency, as movement time (MT) was not significantly different across the six movement directions. Analysis of primary submovement endpoints during this task revealed further direction-dependent differences in users' movement behaviors. Specifically, users tended to end their primary submovements farther from the target (i.e., larger d_{PSE}) when moving up than when moving down, and when moving to the left than when moving to the right. Users also tended to end their primary submovements farther from the target when moving along the depth axis (i.e., toward or away from themselves) than when moving to the right. Finally, participants also tended to spend more absolute time in the primary phase of their movements when reaching to targets along the depth axis (i.e., toward or away from themselves) than when moving to the left or right to targets positioned at a constant depth. Since MT did not differ significantly between these movement directions, this suggests that participants may have spent a greater proportion of MT in the primary phase (i.e., greater percent time to primary submovement endpoint; $PTPSE$)

when moving to targets at varying depths than when moving directly to the left or right of the starting position.

In another study examining 3D pointing movements in VR, Lubos and colleagues [112] had participants reach outward from a central starting point near their sternum to select virtual targets positioned in nine different regions of 3D space. Targets were presented using a VR headset, and users reached to each target using a 6DOF tracker that was attached to their hand. The targets were presented at each location at three different depths, with larger depths requiring participants to reach farther away from their body to select the targets. The primary goal of this study was to analyze patterns of selection errors during reaching tasks performed in VR, but as part of this analysis the authors explored how movement time (MT) changed as a function of movement direction. They found that for this task, MT was significantly larger for movement to targets in the lower positions (i.e., requiring movements away from the body and down) than for the other movement directions. This suggested that for this task, users' movements were less efficient overall when moving to the lower targets than when moving to the upward targets. The authors did not examine other kinematic measures, so it is unclear what underlying changes in movement behavior may have been responsible for this direction-dependent difference in MT.

In a more recent study comparing the kinematic properties of 3D functional movements performed in the real world and VR, Arlati and colleagues [7] had users perform reach-to-grasp movements using their dominant and non-dominant hands to targets positioned at different locations in the vertical plane. The targets were items on either a virtual or physical grocery store shelf, and users stood in front of the shelf and reached to select the items using either their hand or a handheld VR controller. Targets could appear in nine different locations in a three-by-three array, with the items arranged on three shelves (rows) with three items positioned on each shelf (one in each of the three columns). Consequently, although this study was framed as a reach-to-grasp task, the VR version of the task approximated a virtual hand reaching task. In an analysis examining the effects of hand (dominant, non-dominant), condition (real world, real world while holding controller, VR), and movement direction on a selected set of kinematic measures, they found that peak velocity (v_{peak}) during the reaching portion of the movements differed significantly as a function of movement direction. This effect reflected the fact that v_{peak} values were significantly larger for movements performed to the upper left target (requiring the user to move out, up, and to the left) than for movements to the middle-left target (requiring the user to move out and to the left). Significant differences in v_{peak} values were not observed between any of the other conditions. Furthermore, the authors reported no significant condition-by-direction interactions, indicating that there was no significant difference between the physical and VR tasks in how this direction-specific difference emerged. They also examined movement time (MT) and found that this metric did not vary significantly as a function of movement direction. This suggests that for this task, users did not exhibit significant differences in the overall efficiency of their movements across the set of movement directions examined. However, there were some significant higher-order interactions between the factors movement direction and hand, which will be discussed in a later section.

A similar study by Knaut and colleagues [102] also examined some kinematic properties of reaches to targets at different positions in the coronal plane. Specifically, to examine the kinematics of pointing movements performed by stroke patients and healthy controls, the authors had participants reach as quickly and accurately as possible to select either physical targets or similarly positioned virtual targets that were presented using a head-mounted display. Participants reached from a central starting position to select targets at six different positions in the coronal plane. In the virtual environment, these targets were themed as elevator buttons, and participants earned points for performing movements as quickly and accurately as possible. The healthy participants, whose behavior is of interest to our work here, performed the task using only their non-dominant limb. Although the authors focused their analysis on comparing kinematic outcomes between movements to physical and virtual targets, their results also suggest that for movements performed by healthy subjects in both the physical and virtual environments, peak velocity (v_{peak}) may have tended to be largest for ipsilateral movements (on the same side of the body as the performing hand), slightly smaller for movements directly forward, and smallest for movements to contralateral targets (on the opposite side of the body from the performing hand). This trend appears to have been present for both movements to higher and lower targets, with movements to the higher targets generally involving higher peak velocity values than movements to lower targets. Unfortunately, the authors did not explore these comparisons in their analyses, so it is not clear if these differences would have reached statistical significance.

Finally, as part of an effort to extend Fitts' law to account for 3D reaching movements performed in VR, Clark and colleagues [37] examined performance in a discrete goal-directed reaching task that involved reaching from a central starting location to select targets of four different sizes at a range of different locations in 3D space. The targets involved several different movement directions, but they also appeared at several different distances from the starting location. Targets were presented using an Oculus Rift headset, and participants reached to select the targets using a handheld VR controller. Because the principal focus of this study was exploring an extension of Fitts' law, which predicts movement time (MT) given the size of the target and the distance that must be covered to reach it, the analysis focused on analyzing how MT changed as a function of target size, movement distance, and target location. The results suggested that MT varied significantly as a function of movement direction, which was quantified using the spherical coordinate terms inclination angle (i.e., angle away from the vertical plane) and azimuth angle (i.e., angle away from the *x*-axis). Specifically, they found that for larger target sizes, MT tended to be larger when the movement direction was pitched away from participants (i.e., involved movements outward) than when the movement direction was pitched toward participants (i.e., involved movements inward, toward participants). However, the strength of this relationship decreased for smaller target sizes. Their results also suggested that MT tended to be larger for upward compared to downward movements. Unfortunately, since movement direction was not crossed orthogonally with movement distance in this study, some movement directions may have tended to involve targets with larger or smaller movement distances. Consequently, it is difficult to determine if these direction-dependent differences in MT reflect adaptations to movement direction alone, or rather reflect a combined effect of movement direction and movement distance.

1.5.1.2 In Other Related Task Contexts

Several studies to-date have also examined how the kinematic properties of users' reaches change as a function of movement direction in tasks that are similar to virtual hand reaching but impose different constraints on users' movement behaviors. This includes studies examining 3D reaches performed to physical targets, 2D reaching where the hand can only move in the horizontal plane, reciprocal pointing involving repeated selection of two target locations, uncorrected 3D reaching movements, and reaches performed without visual feedback of the hand. Table 1.1 below summarizes the task contexts that have been examined in this body of work and lists the studies to-date that have used kinematic analysis to provide evidence of how the kinematic properties of reaching movements change when users reach in different movement directions during each task.

Together, this body of work reveals several recurring patterns concerning how the kinematic properties of reaching movements change when users reach in different movement directions. First, there is evidence that when users use their right hand to reach outward to select targets at different locations in space, several kinematic properties of their reaches can vary depending on whether their movement direction is angled out and to the *right* or out and to the *left*. Specifically, when users move outward and to the *right*, they tend to exhibit shorter MT [6,22,32,75,100,173], larger v_{peak} [6,22,173,187,193], and smaller $PTPV$ [29,193] (c.f., [100,187]) than when they move outward and to the *left*. Together, this suggests that when using their right hand to move outward and to the *right*, users can take less time to reach targets (MT) while reaching higher speeds (v_{peak}). Notably, the tendency for rightward movements using the right hand to exhibit larger v_{peak} is consistent with results from at least one study examining virtual hand pointing [102]. Users may also tend to exhibit velocity profiles that are less symmetric (smaller $PTPV$) when reaching out and to the right rather than out and to the left, although the opposite pattern (i.e., larger $PTPV$ for movements out and to the right) has also been observed in some task contexts. These differences in the underlying properties of users' movements may manifest in an overall efficiency benefit (smaller MT) for movements out and to the *right*, compared to movements out and to the *left*. To our knowledge, it is not yet clear if the patterns described above also occur in the context of virtual hand pointing.

Table 1.1: Studies that have examined how the kinematic properties of reaching movements change as a function of movement direction, in task contexts similar to virtual hand reaching.

Task Context	Studies
3D reaching to physical targets	Bradshaw et al. (1990) [24]
	Carson et al. (1990) [32]
	Carey (1994) [29]
	Carey et al. (1996) [30]
	Archambault et al. (1999) [6]
	Meischke et al. (2001) [122]
	Lyons et al. (2006) [113]
	Keulen et al. (2007) [97]
	Murata & Iwase (2001) [128]
	Kim et al. (2011) [100]
	Bennett et al. (2012) [21]
	Cha & Myung (2013) [34]
	Burkitt et al. (2017) [25]
	Gutierrez-Herrera et al. (2017) [75]
	Xiao et al. (2019) [193]
	Roberts (2020) [157]
	Aina (2022) [3]
	Bayle et al. (2022) [16]
2D reaching constrained to the horizontal plane	Thompson et al. (2007) [176]
	Berret et al. (2021) [22]
	Waters & Wade (2021) [187]
3D reciprocal pointing between virtual targets	Machuca & Stuerzlinger (2019) [114]
	Batmaz et al. (2019) [14]
	Grossman & Balakrishnan (2004) [74]
Uncorrected 3D reaching movements	Papaxanthis et al. (1998) [143]
	Papaxanthis et al (2003) [142]

	Shemmel et al. (2007) [170]
Reaching without visual feedback of the hand during movements	Stewart et al. (2013) [173] Tomlinson & Sainburg (2012) [179]

There is also evidence that users can exhibit different movement behaviors when they reach either directly downward or directly upward from a central starting position. Specifically, this body of work indicates that compared to upward reaches, downward reaches may exhibit larger d_{PSE} [21,25,113,157] (c.f., [39]), and larger $PTPV$ [142,143] (c.f., [39]). These results suggest that users may opt to end their primary submovements farther from the target (larger d_{PSE}) and achieve movements with more symmetric velocity profiles (larger $PTPV$) when moving down than when moving up. Interestingly, the results concerning d_{PSE} differ from those observed by Clark & Riggs [39] for similar reaching movements performed in VR, highlighting how users may adapt their reaching behaviors differently during real-world and virtual hand reaching. In addition to these findings, there is also evidence that downward movements can exhibit smaller $PTPSE$ than upward movements [113]. Together with the results summarized above, this suggests that compared to upward movements, downward movements may tend to involve a more prolonged primary phase characterized by a longer (and perhaps slower) primary submovement that ends later in the movement.

Other findings suggest that there may be kinematic differences between (1) movements that involve reaching directly to the left or right of the starting position and (2) movements in which users reach directly away from their body along the depth axis. Specifically, compared to movements directly to the left or right, there is evidence that reaches performed directly away from the user may exhibit longer MT [14,74,114:201,176] (c.f., [39,113]), and smaller v_{peak} [176,187]. There is also evidence that reaches away from users can tend to exhibit larger $PTPSE$ than reaches directly to the left or right [176], corroborating a pattern that has been observed for virtual hand pointing [39]. Together, this suggests that when users reach directly away from their body along the depth axis, they may tend to reach a slower top speed (smaller v_{peak}) while opting for movements that contain a more elongated primary submovement (larger $PTPSE$). In some cases, these kinematic differences may in turn lead to a decrement in the overall efficiency of users' movements (larger MT), such that users take more time to select targets at depth than to select targets directly to the left or right of their initial starting position. However, these performance differences may not emerge in all contexts [39,113].

There is also some evidence to suggest that users may exhibit different reaching kinematics when reaching away from their body and *down* than when reaching away from their body and *up*. Specifically, compared to movements that involved reaching out and *up*, movements out and *down* may exhibit smaller MT [34,128] (c.f., [112]), and smaller $PTPV$ [3], suggesting that movements which involve reaching out and *down* may tend to be more efficient overall (smaller MT) and involve less symmetric velocity profiles (smaller $PTPV$) than movements that involve reaching out and *up*. Interetingly, concerning MT, Lubos and colleagues [112] observed precisely the opposite pattern for virtual hand reaching. In their study, users exhibited larger MT when reaching to lower targets than when reaching to higher targets. These conflicting findings could be taken to highlight how users may adapt their movements differently during real-world and virtual hand pointing, but they may also be related to differences in where the lowest targets were positioned in this set of studies. Namely, the lowest targets in the study of Lubos and colleagues [112] were near or below waist height, while the lowest targets in the other studies were positioned higher up in the coronal plane.

Finally, there may also be kinematic differences between movements that involve reaching directly to the left or right of a central starting position. Specifically, there is evidence that when these movements involve reaching *toward* the side of the reaching arm (e.g., movements to the right using the right hand), they may exhibit smaller MT [24,30,122] (c.f., [97]), larger v_{peak} [30,122] and larger $PTPV$ [30,122] than movements that involve reaching *away from* the side of the reaching arm. This pattern has been taken to reflect an overall performance benefit for abductive reaching movements, which involve reaching outward away from the body midline, compared to adductive movements, which involve reaching inward toward the body midline. However, at least one study has instead shown an MT benefit for adductive (inward) movements compared to abductive (outward) movements [97]. Furthermore, in a study focused on center-out reaching movements performed in VR, Clark and Riggs [39] found no significant difference in MT values between adductive and abductive movements, but they did observe that v_{peak} was significantly larger for movements to the right (abductive) than for movements to the left (adductive). This suggests that users may achieve faster speeds when performing abductive compared to adductive virtual hand reaches, at least for center-out reaches that begin near the body midline.

1.5.2 Effects of Hand Dominance

1.5.2.1 In Virtual Hand Reaching Tasks

Most of the work to-date examining users' movement behaviors during virtual hand reaching has focused on movements performed using the dominant limb (e.g., [37,39,102,112]). Nonetheless, there has been some limited work comparing the kinematic properties of virtual hand reaching movements performed using either the dominant or non-dominant hands. Although these studies were primarily designed to address other research questions, the kinematic results they reported provide an initial look at how the kinematic properties of users' reaching behaviors can be different when users reach using the dominant and non-dominant limbs.

First, as part of a study to explore the feasibility of VR-based eye-hand coordination tasks, Batmaz and colleagues [15] (study 1) had participants use a handheld controller to reach between virtual targets in an evenly spaced array that was aligned with either the vertical or the horizonal plane. The targets and cursor could take on varying sizes, and movements between targets could require users to cover different movement distances. The targets were highlighted one by one in a random sequence, and participants selected targets sequentially, such that the movement to target n began at target $n-1$. As in a typical virtual hand reaching task, participants were instructed to select each target as quickly and accurately as possible. In this context, they found that movements performed using the dominant hand tended to exhibit significantly smaller MT than movements using the non-dominant hand. This suggested that overall, movements performed using the dominant hand were generally more efficient than similar movements using the non-dominant hand. However, the authors did not examine other kinematic measures, so it is not clear what underlying changes in the structure of users' reaching movements may have been responsible for this hand-specific difference in overall movement efficiency. Furthermore, due to the scope of its research questions, this work did not treat movement direction as an independent variable. It is therefore not clear if users may have adapted their movement behaviors as a function of movement direction differently depending on if they were reaching using their dominant or their non-dominant hand.

The other set of informative results concerning the influence of hand dominance on virtual hand pointing movements comes from the study by Arlati and colleagues [7], which was described in section 1.5.1.1 above. The goal of this study was to compare the kinematic properties of 3D functional movements that were performed either in the real world or using a modern VR system (HTC Vive). Participants performed simulated reach-to-grasp movements that involved using their dominant or non-dominant hands to select targets positioned at different locations in the vertical plane (i.e., items on a virtual grocery store shelf). In this context, there were no significant effects of hand dominance on MT or v_{peak}. This suggested that when averaged across all movement directions, movements using the dominant and non-dominant hands did not exhibit significant differences in efficiency or speed. However, the effect of movement direction on both MT and v_{peak} differed significantly between movements performed using the dominant and non-dominant hands. This interaction effect reflected the fact that when users reached to the target that required them to reach out, down, and toward the left side of their body, movements using the non-dominant hand exhibited longer MT and smaller v_{peak} than movements using the dominant hand. The analogous differences did not reach significance for the other movement directions, suggesting that the dominant arm only enjoyed a speed and efficiency advantage compared to the non-dominant arm for movements to this one target location. These findings highlight one way in which users may adapt their movement behaviors differently as a function of movement direction when they reach using their dominant and non-dominant hands.

1.5.2.2 In Other Related Task Contexts

Additional studies to-date have examined kinematic differences between reaches using the dominant and non-dominant hands in tasks that are similar to virtual hand reaching but imposed different constraints on users' movement behaviors. This includes studies examining 3D reaching movements to physical targets, 2D reaches during which the hand is constrained to the horizontal plane, reach-to-grasp movements, movements performed without visual feedback of the hand, and reciprocal pointing tasks in which the user repeatedly moves between two target locations. Table 1.2 below summarizes the task contexts that have been examined in this body of work and lists the studies to-date that have examined how the kinematic properties of reaching movements change as a function of hand dominance during each task.

Table 1.2: Studies that have examined how the kinematic properties of reaching movements change as a function of hand dominance, in task contexts similar to virtual hand reaching.

Task Context	Studies
3D reaching to physical targets	Bradshaw et al. (1990) [24] Carey (1994) [29] Keulen et al. (2007) [97] Kim et al. (2011) [100] Johnstone (2015) [88] Xiao et al. (2019) [193] Bayle et al. (2022) [16]
2D reaching constrained to the horizontal plane	Van Doorn (2008) [48] Claudio & Teixeira (2012) [41] Jones et al. (2021) [89] Goh et al. (2022) [70] Wijeyaratnam et al. (2022) [189]
Reach-to-grasp movements	Stins et al. (2001) [174] Flindall et al. (2014) [63]
2D reciprocal pointing movements	Kabbash et al. (1993) [91]
Reaching without visual feedback of the hand during movements	Tomlinson & Sainburg (2012) [179] Schaffer & Sainburg (2017) [165]

This body of work highlights several ways in which users may move differently when they reach using their dominant and non-dominant arms. Specifically, there is evidence that compared to movements using the non-dominant arm, reaches with the dominant arm can sometimes exhibit smaller MT [24,41,48,63,70,88,91,174] (c.f., [189]), larger $PTPV$ [88,174] (c.f., [189,193]), larger v_{peak} [88] (c.f., [63,165,189,193]), and may also tend to follow more curved paths through space [16,70,89,179,193] (c.f., [165]). Together, these results suggest that movements using the dominant arm may tend to reach higher top speeds (larger v_{peak}), although this benefit may not emerge in all task conditions. Furthermore, dominant arm movements may tend to follow straighter paths through space and involve more symmetric velocity profiles (larger $PTPV$), implying that they may rely less on late corrective submovements than movements using the non-dominant arm. These kinematic differences between movements performed by the two limbs may contribute to interlimb differences in the overall efficiency of users' movements, such that movements using the dominant arm may be more efficient (exhibit smaller MT) than movements using the non-dominant arm.

Notably, most of the work to-date has focused on examining differences between the properties of reaching movements performed using the dominant and non-dominant limbs, either by examining movements performed in only one direction (e.g., [48]) or averaging across movements performed in several different directions (e.g., [89]). Consequently, while there is considerable work to suggest how users may move differently when they reach using their dominant and non-dominant arms, much less work has been devoted to understanding if these interlimb differences may manifest differently when users reach in different *movement directions*. In other words, relatively little work has considered if and how users may adapt differently to changes in movement direction when they reach using their dominant and non-dominant arms. However, at least three sets of studies to-date have taken some initial steps toward answering this question.

First, there is some evidence that when users reach outward in different directions to select targets positioned in the sagittal plane, the kinematic properties of their reaches may change differently as a function of movement direction depending on which hand they use to perform the movements. For example, Tomlinson & Sainburg [179] had participants perform 3D reaches to targets at three different locations in the sagittal plane. To select the targets, users needed to reach *out and up*, *directly out* along the depth axis, or *out and down*, with most of the movement occurring within the sagittal plane. Users reached to select the targets using their dominant and non-dominant limbs, and they were instructed to move as quickly and accurately as possible to select each target. In a deviation from the typical conditions present during virtual hand reaching, visual feedback of the hand was occluded during the movements. In this context, users' hands tended to follow more curved paths through space when reaching *out and up* than when reaching *directly out* or *out and down* [179]. Interestingly, this effect was more pronounced for movements using the non-dominant hand than for movements using the dominant hand. Specifically, as target height increased, trajectory path curvature increased considerably more for movements using the non-dominant arm than for movements using the dominant arm. This points to one way in which the kinematic properties of reaching movements can change differently as a function of movement direction when users reach using the dominant compared to the non-dominant hand. Namely, users may be able to maintain straighter trajectory paths when reaching *out and up* using their dominant limb, while similar movements using the non-dominant limb may follow a less direct path through space. A later study by Schaffer & Sainburg [165] used a similar movement task to examine reaches performed in different directions to targets positioned in the *horizontal* plane. Again, movements in this task were performed without visual feedback of the hand. In this context, they found that both trajectory curvature and v_{peak} varied significantly as a function of movement direction, but there were no significant hand by movement direction interaction effects. This suggests that in some cases, users may adapt their movement behaviors as a function of movement direction similarly when they reach using their dominant and non-dominant hands.

Second, there is some evidence that users may exhibit hand-specific adaptations to changes in movement direction when they reach directly to the left or right of a central starting position to select targets positioned in the horizontal plane. Namely, in this context, users can sometimes exhibit shorter MT for adductive reaching movements (i.e., reaches inward toward the body midline) than for abductive reaches (i.e., reaches away from the body midline [97]; c.f., [24,30,122]). This means that when users reach using their right hand, they may perform more efficient movements (lower MT) when moving directly to the left than when moving to the right. Conversely, for reaches performed using the left hand, users may tend to achieve more efficient movements when moving directly to the right than when moving to the left. However, some other studies report the opposite pattern, with abductive movements exhibiting shorter MT than adductive movements [24,30,122]. These diverging results suggest that this pattern hand-specific adaptation to differences in movement direction may emerge differently in different task contexts.

Finally, there is also evidence that when users reach outward in different directions to select targets positioned in the horizontal plane, their movement behaviors can change depending on whether their movement direction is angled *toward* or *away from* the side of the reaching arm. Specifically, for movements with both the dominant and non-dominant hands, users may exhibit larger v_{peak} [187,193] and smaller $PTPV$ [29,193] (c.f., [100,187]) when they reach outward and *toward* the side of their reaching arm, compared to when they reach outward and *away from* the side of their reaching arm.

This means that when users reach using either their dominant or non-dominant hands, they may tend to move with a higher top speed (larger v_{peak}) when moving outward and toward the side of the reaching hand than when moving outward and away from the side of the reaching hand. Movements out and *toward* the side of the reaching hand may also tend to exhibit velocity profiles that are less symmetric (smaller $PTPV$) than movements outward and to the left, although the opposite pattern has been observed in some studies [100,187]. Smaller $PTPV$ could imply that movements out and *toward* the reaching hand may rely more heavily on late feedback-based corrective submovements. Conversely, larger $PTPV$ would imply that movements out and *toward* the reaching hand rely *less* on corrective submovements than movements out and *away* from the reaching hand. This latter pattern may be more consistent with the results from work examining movements using only the right hand, which tend to show performance benefits for movements out and *toward* the side of the reaching hand. Namely, in these studies, movements out and to the right (*toward* the reaching hand) exhibited shorter MT [6,22,75,173] than movements out and to the left (*away* from the reaching hand).

1.5.3 Effects of Interaction Hemispace

1.5.3.1 In Virtual Hand Reaching Tasks

Relatively little of the work to-date examining virtual hand reaching movements has studied how the kinematic properties of users' movements change depending on the *hemispace* in which those movements occur (i.e., contralateral or ipsilateral to the reaching arm). However, the limited findings to-date still provide some initial hints. Most of this evidence comes from studies that examined center-out reaching movements, in which users began with their hand at a starting point near their body midline and reached to select targets at different locations in 3D space. In these tasks, reaches to the left or right of the starting position occurred entirely within the hemispace contralateral or ipsilateral to the reaching arm, depending on which hand was used to perform the movements. For example, when using the right hand to perform center-out reaches, movements to the right occur in the hemispace *ipsilateral* to the reaching arm (i.e., on the right side of the body), while reaches to the left occur in the hemispace *contralateral* to the reaching arm (on the left side of the body).

In one such study, Clark and Riggs [39] had users perform discrete 3D reaching movements from a central starting location to targets positioned in six different directions in a VR environment. These targets required users to move primarily along the horizontal axis (i.e., directly to the left or right of the starting position), vertical axis (directly up or down), and depth axis (directly toward or away from the user). Since all participants used their right hand to select the targets, movements to the right were performed in the hemispace *ipsilateral* to the reaching arm, while movements to the left occurred in the hemispace *contralateral* to the reaching arm. In this context, movements to the right (ipsilateral) exhibited significantly larger peak velocity (v_{peak}) than movements to the left (contralateral). Furthermore, users also ended their primary submovements significantly farther from the target (i.e., larger d_{PSE}) when they reached to the left than when they reached to the right. However, despite these kinematic differences, there was no significant difference in MT between movements to the right (ipsilateral) and movements to the left (contralateral). This suggests that users achieved their movements with similar overall efficiency (MT) when reaching to the left and right, but they may have used different strategies to achieve that same level of performance across these two conditions.

In another study examining center-out virtual hand reaches, Knaut and colleagues [102] had participants reach as quickly and accurately as possible to select physical and virtual targets at 6 different positions in the coronal plane. Targets were positioned in three rows and two columns, with one column of targets aligned with the body midline and the remaining two columns positioned to the left and right of the body midline, respectively. In the virtual environment, these targets were themed as elevator buttons, and participants earned points for performing movements as quickly and accurately as possible. A principal goal of this study was to compare the kinematics of pointing movements performed by stroke patients and healthy controls in both physical and virtual environments, but the results from healthy participants are most applicable to our work here. These results included a trend suggesting that users tended to exhibit larger v_{peak} when they reached to targets in the hemispace *ipsilateral* to the reaching hand than when they reached in the *contralateral* hemispace. There was also a trend suggesting that users may exhibit larger v_{peak} when reaching to targets in the top row than when reaching to targets in the bottom row. This difference in v_{peak} values between high and low targets seems to have been similar regardless of the hemispace in which the movements occurred, suggesting that this effect of movement direction on v_{peak} may not have manifested differently for movements in the contralateral and ipsilateral hemispaces. However, the authors did not explicitly examine either of these patterns in their statistical analysis, so it is difficult to draw strong conclusions from these results alone.

In a more recent study examining center-out reaching movements in VR, Lubos and colleagues [112] had participants reach outward from a central starting point near their sternum to select virtual targets positioned in nine different regions of 3D space. Targets were presented using a VR headset, and users reached to each target using their dominant hand while a 6DOF tracker was attached to their hand. The targets were presented at each location at three different depths, with larger depths requiring participants to reach farther away from their body to select the targets. The primary goal of this study was to analyze patterns of selection errors during virtual hand reaching, but as part of this analysis the authors also explored how movement time (MT) changed as a function of movement direction. In this context, they did not report any significant differences in MT between movements performed to targets on the right side of the body (ipsilateral) and movements to targets on the left side (contralateral). This suggests that, at least for center-out reaches in the directions considered in this task, users may achieve movements with the same overall efficiency (MT) when reaching in the contralateral and ipsilateral hemispaces.

Most recently, in the study by Arlati and colleagues [7] described in section 1.5.1.1 above, users used their dominant and non-dominant arms to reach to targets at different locations in the vertical plane. In this context, they found that when users reached to targets in the bottom left location, they exhibited significantly larger MT when using their right arm than when they selected the same target using their left arm. This suggests that for movements to this one target location, users may have exhibited smaller MT when reaching occurred in the *contralateral* hemispace (reaching to the lower left using the right hand) than when the movement occurred in the *ipsilateral* hemispace (reaching to the lower left using the right hand). However, since the "contralateral" reaches in this case were performed using the dominant hand, while "ipsilateral" reaches to this target were performed using the non-dominant hand, it is difficult to determine if this pattern of results reflects a hemispace-dependent movement adaptation, or if it rather can be attributed to differences between movements performed using the dominant and non-dominant limbs.

1.5.3.2 In Other Related Task Contexts

Further evidence concerning how the kinematic properties of users' reaching behaviors can change as a function of hemispace comes from studies of movement tasks that are similar to virtual hand reaching but impose slightly different constraints on users' movements. These include studies examining 3D reaches performed to physical targets, 2D reaches in which the user's hand is constrained to the horizontal plane, and reaches performed without visual feedback of the hand during movements. Table 1.3 below summarizes the tasks that have been examined in this body of work and lists the studies to-date that have directly or indirectly examined hemispace-dependent differences in users' movement behaviors.

Like the work to-date examining hemispace-dependent differences in virtual hand pointing, most of these studies have focused on center-out reaching movements. Recall that in center-out movements, reaches to the right or left of the central starting position can occur entirely within the hemispace contralateral or ipsilateral to the reaching arm, depending on which hand is used to perform the movements. In this context, work to-date has found that compared to reaching movements performed in the hemispace *contralateral* to the reaching arm, reaches into the *ipsilateral* hemispace may exhibit smaller MT [6,22,28,30,32,34,61,75,100,122,173], larger v_{peak} [6,22,28,30,122,173,193], and larger $PTPV$ [30,100,187]. This suggests that when users reach into the *ipsilateral* hemispace, they may achieve higher maximum speeds (larger v_{peak}) while exhibiting more symmetric velocity profiles (larger $PTPV$). These kinematic differences may lead to hemispace-dependent differences in users' overall movement efficiency (smaller MT), with reaches into the ipsilateral hemispace requiring less time to complete than reaches into the contralateral hemispace.

Notably, most of the work described above compared reaches performed in two potential movement directions, with one movement direction taking the hand into the contralateral hemispace and the other involving reaching in the ipsilateral hemispace. Since movements in each hemispace only involved one movement direction, this work does not provide any hints as to how movement direction and hemispace may interact to influence users' movement behaviors. However, a few studies have examined movements performed in multiple directions in each hemispace. Although this work has still only examined a limited number of movement directions in each hemispace, it still points to some ways that users may adapt their movement behaviors differently as a function of movement direction when they reach in the contralateral compared to the ipsilateral hemispace.

Table 1.3: Studies that have examined how the kinematic properties of reaching movements change as a function of interaction hemispace, in task contexts similar to virtual hand reaching.

Task Context	Studies
3D reaching to physical targets	Fisk & Goodale (1985) [61] Bradshaw et al. (1990) [24] Carson et al. (1990) [32] Carey (1994) [29] Carey et al. (1996) [30] Archambault et al. (1999) [6] Mieschke et al. (2001) [122] Keulen et al. (2007) [97] Kim et al. (2011) [100] Cha & Myung (2013) [34] Carey et al. (2015) [28] Gutierrez-Herrera et al. (2017) [75] Xiao et al. (2019) [193]
2D reaching constrained to the horizontal plane	Waters & Wade (2021) [187] Berret et al. (2021) [22]
Reaching without visual feedback of the hand during movements	Stewart et al. (2013) [173]

In one such study, Carson and colleagues [32] had participants use their left or right hand to reach from a central starting position and select physical targets at eight different positions in the vertical plane. Targets were arranged in an array with two rows and four columns. The whole target arrangement was centered on the user's body midline, such that two columns of targets were located on the left side of the body midline and the remaining targets were positioned to the right of the body midline. Consistent with the other studies summarized above, they found that reaches into the hemispace *ipsilateral* to the reaching arm exhibited shorter MT than reaches into the *contralateral* hemispace. However, they also found that the size of both the MT advantage for ipsilateral reaches and the MT cost for contralateral reaches varied depending on how far the targets were from the body midline. Namely, MT was smallest for targets that were positioned farthest from the body midline in the *ipsilateral* hemispace, and largest for targets that were positioned farthest from the body midline in the *contralateral* hemispace. For the target locations in between, MT increased following a graded trend as *movement direction* shifted from ipsilateral to contralateral space. Without other kinematic measures, it is not clear precisely why this pattern of results may have occurred. However, this finding does suggest that hemispace-dependent patterns in users' movement behavior may depend on the direction in which a user is moving, rather than applying similarly for any movements that occur in a given hemispace. This is intuitive, considering that the biomechanical mechanisms whereby hemispace is expected to influence users' movement behaviors (e.g., adaptations to differences in limb inertia) are likely not uniform for all possible movements within a given hemispace.

Keulen and colleagues [97] also examined movements in multiple directions that occurred in either the contralateral or ipsilateral hemispace. Specifically, in a study exploring how distractor interference influences reaching movements, they had right-handed participants use their right hand to reach to targets at different locations in the vertical plane. Targets were presented and selected using a touchscreen monitor, and distractor targets appeared at different locations to the left or right of the target location. Reaching movements either (1) began at the body centerline and involved reaching to a target directly to the left or right, or (2) began on the left or right side of the body and involved reaching inward to a target aligned with the body centerline. With this arrangement, users performed reaching movements in two different directions (outward and inward) in the hemispaces contralateral (left) and ipsilateral (right) to the reaching arm. They found that for movements in the contralateral (left) hemispace, users exhibited significantly smaller MT when they reached *outward* than when they reached inward. However, for reaches in the ipsilateral (right) hemispace, users exhibited shorter movement times when moving *inward* than when moving outward. Notably, both *direction*/*hemispace* conditions that exhibited shorter MT required users to perform *adductive* arm movements, which involve closing the arm inward toward the body. Conversely, both conditions that exhibited longer MT required users to perform *abductive* arm movements, which involve opening the arm up away from the body. This suggests that in some contexts, users may achieve greater overall movement efficiency (i.e., smaller MT) when they perform reaches that involve *adductive* movements rather than *abductive* movements. This highlights one way that users may adapt their movement behaviors differently to changes in movement direction depending on the hemispace in which their movements occur.

Finally, early work by Bradshaw and colleagues [24] also examined reaching movements performed in multiple directions within a given hemispace. However, this work focused only on reaches that occurred entirely within the hemispace *ipsilateral* to the reaching arm. Specifically, they had participants use their right or left hand to reach to targets that were positioned directly to the left or right of a specified starting position in the horizontal plane. The starting position and targets were arranged so that reaches with each hand occurred entirely in the hemispace ipsilateral to the reaching hand (i.e., in the left hemispace for left hand movements, and in the right hemispace for the right hand). In this context, they found that participants tended to exhibit shorter MT when they reached outward, away from the body midline (i.e., reaching to the left in the left hemispace, or to the right in the right hemispace) than when they reached inward, toward the body midline (i.e., to the right in the left hemispace, or to the left in the right hemispace). This suggests that in some contexts, users may tend to achieve more efficient movements (smaller MT) when performing reaches that involve *abductive* arm movements (e.g., reaching to the right in the right hemispace) than when performing reaches that require *adductive* arm movements (e.g., reaching to the left in the right hemispace). Notably, Keulen and colleagues [97] observed precisely the opposite pattern for reaches to targets in the vertical plane. This may be due to differences between the two studies in the arm configurations that users needed to adopt to reach targets positioned in the coronal plane [97] rather than the horizontal plane [24]. In any case, it is not yet clear which (if any) of these patterns may emerge during virtual hand reaching movements.

1.5.4 Effects of Arm Length

To our knowledge, no studies to-date have yet explored if and how individual differences in arm length influence the kinematic properties of reaching movements in the real world or in VR. Indeed, there has been very little work examining the relationship between arm anthropometry and reaching movement kinematics in any context. Therefore, it is not yet clear if and how the effect of movement direction on reaching movement kinematics may vary across users depending on their arm length. However, limited work addressing a few related topics does provide some initial hints. This work suggests that, at least in some contexts, the kinematic properties of users' arm movements may vary depending on a users' arm length.

1.5.4.1 Tool Use and Embodiment Studies

The first set of informative results comes from work examining tool embodiment. In this body of work, kinematic metrics have been used to test the hypothesis that users update their body schema (i.e., an internal representation of their limbs) when they perform reaching tasks using handheld tools. As part of one such study, Martel and colleagues [116] had users perform reach-to-grasp movements to targets in the horizontal plane using either their free hand or a handheld mechanical grasping tool. Free hand reaches were performed using the right arm and involved reaching from a starting position aligned with the user's shoulder in one of two directions (i.e., directly away from the starting position in depth, or directly to the left of the starting position). Reaches using the grabber tool were also performed using the right arm, but only involved reaching away from the starting position in depth. Users reached without visual feedback of their hand or the target object, and they localized the target via somatosensation by gently touching it with their non-reaching hand throughout each movement. Importantly for our purposes, Martel and colleagues examined the correlation between users' arm length and the kinematic properties of the transport phase of the reach-to-grasp task, which is roughly analogous to a goal-directed reaching movement. In this context, they found that arm length was moderately correlated with several kinematic properties of users' reaches, such that users with longer arms exhibited slightly smaller peak velocity (v_{peak}) and peak acceleration and tended to reach these kinematic landmarks slightly later in their movements (implying larger $PTPV$).

In a recent critical review assessing the strength of evidence in support of the tool embodiment hypothesis, Bell and Macuga [20] performed a secondary analysis that incorporated data from both [116] and a subsequent study using the same task [117]. This analysis revealed that the relationships between arm length and reaching kinematics that were reported by Martel and colleagues [116] emerged for reaches that involved moving across the body (i.e., moving directly to the left from the starting position), but not for reaches that involved moving away from the user in depth. Specifically, for reaches across the body, users with longer arms tended to exhibit slightly smaller peak velocity and peak acceleration. However, when users instead reached away from themselves in depth, there were no significant correlations between arm length and reaching movement kinematics. This suggests that when users use their right hand to reach from right to left across their body, some kinematic properties of their reaches can vary depending on their arm length. However, since this body of work examined reaches performed without visual feedback of the arm and focused on the transport phase of reach-to-grasp movements, rather than goal-directed reaches (which do not involve a grasping component), it is not clear if these past findings may generalize to the present task context.

Research examining how users incorporate handheld tools into their motor system has also examined how the kinematic properties of reaching movements change when users reach using handheld pointers of varying length. While these studies did not examine the effects of the user's arm length on reaching kinematics per se, they do suggest that when the length of a limb segment is artificially increased (i.e., increasing the reach of the finger by attaching a rod or using a handheld tool), the kinematic properties of users' reaches can change as users adapt their behaviors to these artificial changes in arm length. For example, Burkitt and colleagues [25] examined the kinematic properties of vertical reaching movements in which users reached upward or downward from a central starting position to targets that were positioned at one of three potential distances from the starting point. Users either performed these reaches using just their finger, or reached using rod extensions of two different lengths (150 and 300 mm) that were attached to their finger. This design effectively manipulated the length of one limb segment (i.e., finger length) within-subjects. In this context. Burkitt and colleagues found that users adopted different reaching strategies in the three different limb segment length conditions. Namely, they found that users were able to take advantage of the artificially lengthened finger to minimize their energy expenditure by adjusting how much they engaged their shoulder and elbow to perform reaches. Notably, these strategic differences between the different segment length conditions coincided with differences in several kinematic properties of users' reaches, such that users tended to exhibit longer MT and larger d_{PSE} when they reached using the rods than when they reached using their finger. Similar studies using handheld pointers have also found that the kinematic properties of users' reaches can change when users reach with pointers of different length. Namely, there is evidence that as pointer length increases, users can exhibit larger MT [10,181] and larger v_{peak} [181]. Together, these findings are consistent with the idea that users can account for limb segment length when optimizing their reaching behaviors, and these adaptations can influence the kinematic properties of their reaches.

1.5.4.2 Non-Reaching Tasks

The second set of informative results comes from studies that have examined the relationship between arm length and the kinematic properties of non-goal-directed arm movements. These tasks impose different constraints on users' movements than those involved in goal-directed reaching, as a result the findings from these tasks may or may not generalize to goal-directed reaches. However, results from these related tasks can nonetheless provide some hints as to how individual differences in arm length may influence reaching kinematics during goal-directed reaching.

For example, Wingrave and colleagues [190] examined the relationship between arm length and movement behaviors during ray-casting interactions, in which users use a virtual laser pointer that extends outward from their hand to select distant objects at various locations in a VR environment. As part of a study exploring how individual differences influence users' experiences and performance during ray-cast pointing, they examined how arm length and various other demographic characteristics influenced how long it took users to select objects with the virtual pointer (i.e. analogous to MT). They found that users with longer arms tended to take less time to complete ray-casting selections (i.e., smaller MT), but this relationship only reached significance for male users. For female users, there was no significant relationship between arm length and MT.

A few early studies in the biomechanics literature have also examined the relationship between arm length and peak hand speed (i.e., v_{peak}) during tasks that involve basic flexion or extension of the arm. These tasks were different from goal-directed reaching in that users were not asked to reach to a particular location in space. In one such study, Less [108] examined the effect of arm length and mass on the kinematic and kinetic properties of adductive (i.e., inward) arm movements that were performed in the horizontal plane without aiming toward a specific target. In this context, they found a moderate positive relationship between arm length and v_{peak}, such that participants with longer arms tended to achieve slightly larger peak speeds than participants with shorter arms. However, other early work involving similar tasks found no significant relationship between arm length and v_{peak}. Namely, Rasch [155] examined the relationship between arm length and reaching speed for voluntary movements that involved moving a handheld post in the horizontal plane. In this context, they found a small but not significant relationship between arm length and v_{peak}, such that people with longer arms tended to move slightly slower. Similarly, Henry and Whitley [82] examined lateral arm movements that involved sweeping the arm through 90 degrees in the horizontal plane. In this context, they found no significant relationship between arm length and movement speed. Together, these early results suggest that users with longer arms may sometimes achieve larger v_{peak}. However, this benefit may be highly context-specific, and it may or may not emerge in the context of goal-directed reaching.

1.6 Remaining Questions

In summary, some work to-date has examined how *movement direction*, *hand dominance*, and *hemispace* independently influence the kinematic properties of goal-directed reaches, and a few studies have examined two-way interactions among these factors. Of these studies, relatively few have examined goal-directed reaches performed in VR (i.e., "virtual hand reaches"). Rather, most have examined reaches to real world targets, often under constraints that differ from those involved in the unconstrained 3D reaching behaviors that comprise virtual hand interactions (e.g., 2D reaches with the hand constrained to the horizontal plane). Furthermore, relatively few studies have examined how *arm length* influences movement kinematics, and the limited work that has examined this relationship focused on tasks other than goal-directed reaching. Although these studies do provide some useful hints as to how users may adapt their reaching behaviors during virtual hand reaching, we can be less confident that patterns of adaptation observed in task contexts with different constraints will generalize to virtual hand reaching.

To our knowledge, no studies to-date have yet examined if and how the factors *movement direction*, *hand dominance*, and *hemispace* may interact to influence the kinematic properties of goal-directed reaches, either in the physical world or in VR. Furthermore, no work to-date has examined if and how the joint influence of these three factors on reaching kinematics may vary across different individual users, and if the effects of these factors emerge differently for users with different *arm lengths*. In the present work, we began to address these gaps by answering the following research questions:

1. Do the kinematic properties of users' virtual hand reaching movements change when users reach in different *movement directions*?
2. Do some *direction*-dependent adaptations in users' reaching kinematics emerge differently depending on which *hand* is used to perform movements and/or the *hemispace* in which movements occur?
3. How do the kinematic properties of virtual hand reaching movements change when users encounter different values of these three task properties?
4. How do the effects of *movement direction*, *hand,* and *hemispace* on reaching kinematics vary across different individuals?
5. Do individual differences in *arm length* influence how *movement direction*, *hand,* and *hemispace* influence reaching kinematics across different individuals?

As mentioned briefly in section 1.2, answering these questions would bolster numerous research and design efforts at the intersection of human movement science and virtual reality. For work geared toward improving the user experience of VR interfaces, understanding how users' reaching behaviors change as a function of movement direction when they reach on either side of their body using either hand would provide unique insights into how users behave while interacting with emerging consumer VR interfaces. This can be used to enhance predictive models of motor behavior and to better anticipate how users will move while interacting with VR interfaces, by providing top-down information about users' reaching behaviors that can supplement data-driven bottom-up approaches to anticipating users' reaching behaviors (e.g., [81]). In the near term, addressing these questions can also inform ongoing efforts to extend Fitts' law [62] to predict movement time (MT) for unconstrained 3D reaching movements (e.g., [37,114]), by accounting for how MT changes as a function of movement direction during these movements.

For laboratory work aimed at understanding human motor control processes (e.g., [51,54,55]), addressing these questions would help to reveal if and how effects of movement direction on reaching kinematics that have been observed in past work may be different depending on the hand used to perform movements and/or the side of the body on which movements occur. Addressing these questions would also reveal if and how these effects may emerge differently for different individual users depending on the length of their arms. Specifically, as summarized in section 1.5.1 above, past work examining the kinematic properties of reaching movements performed in the real world and VR has observed specific patterns concerning how users adapt their reaching behaviors when they reach in different movement directions (e.g., [113,139]). These observations have played a critical role in advancing our understanding of the human motor system and developing useful theories concerning the control mechanisms responsible for human reaching movements (e.g., the multiple process model of goal-directed reaching; [51,54,55]). By revealing if and how the observations on which these theories are based may vary across different task contexts or individual users, the present work will provide new observations to be accounted for by established motor control theories.

Finally, and perhaps most critically, addressing these gaps would support work in several specific application areas where KA techniques show promise for answering questions about users' movement behaviors in VR. These include monitoring patients' progress during VR-based motor rehabilitation (e.g., [144,164]) and monitoring learners' progress during VR-based motor skills training (e.g., [1,153]). In both these contexts, the present work would provide a detailed quantitative account of how kinematic measures can be expected to change as a function of movement direction for reaches performed in either hemispace using either hand, and how the joint influence of these factors on reaching kinematics may be different for users with different arm lengths. This understanding can be used to interpret kinematic results obtained in these contexts more precisely.

For example, in the stroke rehabilitation space, VR-based therapies have shown promise as a means of helping stroke patients to regain arm function [44,47,57,58,68,106,107,119,127]. At the same time, there has been considerable movement toward using kinematic analyses of reaching movements and other activities to monitor arm function recovery in these patients [130,169], since these analyses can overcome many of the limitations of traditional assessment techniques ([103,148]). Indeed, several of the kinematic metrics that we examine in the present work have shown considerable promise for use in assessing stroke patients [94,126,169]. Consequently, consumer VR systems could eventually be used to both deliver stroke rehabilitation programs [144] and administer kinematic assessments to monitor patients' progress [92], possibly as part of future VR-based telerehabilitation programs [98,144,164,184]. In this context, understanding if and how common kinematic analysis metrics change as a function of movement direction, hand, and hemispace (and if the effect of these factors depends on arm length) would reveal if researchers will need to account for these factors when interpreting the results of future kinematic assessments (see e.g., [77]). For example, if a researcher notices that a patient is exhibiting smaller $SPARC$ values when reaching in one direction than when reaching in another, it would be useful to know if this difference also emerges in healthy participants with similar anthropometric characteristics, or if it rather reflects a stroke-related performance deficit that is not typically observed in similar healthy individuals.

1.7 Overview of the Remaining Chapters

In Chapter 2, we report an exploratory study that examined how six kinematic metrics (MT, v_{peak}, $PTPV$, d_{PSE}, $PTPSE$, and $SPARC$) varied across reaches in five different movement directions, and if/how these direction-dependent differences in reaching kinematics emerge differently for each combination of hand and hemispace (RQs 1-3). In Chapter 3, we further explore the most prominent effects identified in Chapter 2 by examining a larger number of movement directions, providing a more fine-grained account of these effects. In Chapter 4, we examine how these effects emerge differently for different individual users, and if/how these effects emerge differently depending on a user's arm length (RQs 4 and 5). Finally, in Chapter 5, we provide an integrated discussion of the findings from these three studies, including practical and theoretical implications and opportunities for future work.

2 Study 1: Exploring the Effects of Direction, Hand, and Hemispace

To begin addressing the research gaps identified in Chapter 1, we first performed an exploratory study to examine if and how the kinematic properties of users' reaching movements changed when users reached in a set of five different movement directions in a VR environment. Users reached in each direction using their dominant and non-dominant hands, and these movements occurred in the hemispaces contralateral and ipsilateral to their reaching arm. This arrangement was designed to address the following research questions:

1. Do the kinematic properties of users' virtual hand reaching movements change when users reach in different *movement directions*?
2. Do some *direction*-dependent adaptations in users' reaching kinematics emerge differently depending on which *hand* is used to perform movements and/or the *hemispace* in which movements occur?
3. How do the kinematic properties of virtual hand reaching movements change when users encounter different values of these three task properties?

2.1 Methods

2.1.1 Participants

This study included 20 participants recruited from the undergraduate, graduate student, and employee population at the University of Virginia (7 female, mean age = 23.6, range = 18-31). All participants had normal or corrected-to-normal vision and reported having no ailments that impacted their arm mobility. All participants expressed a strong right-hand preference, with scores greater than 40 (M = 78.95, SD = 14.35) on the Edinburgh Handedness Inventory [138]. Five participants reported having had some previous experience with the Oculus Quest or another consumer VR headset, while the remaining participants reported having no previous experience with VR.

2.1.2 Materials

The study was performed using a Meta Quest 2 head-mounted display (Meta Inc.) running custom software built in Unity. The headset had a horizontal field of view of approximately 89 degrees and a vertical FOV of approximately 93 degrees. The virtual environment was rendered using the onboard hardware in the VR headset. Throughout the study, participants used the included 160g handheld Oculus touch controllers to interact with the virtual environment. The experiment was performed in a 2.90m by 2.38m room with the layout depicted in Figure 2.1 below. To minimize any effects of posture adjustments on arm movement kinematics, participants remained seated in a comfortable stationary chair that was secured to the floor in the experimental chamber. This also ensured that the headset's tracking cameras had the same view of the physical environment across all participants and that participants had ample room to perform reaching movements during the study without colliding with any obstacles in the physical environment. The experimenter sat at a desk to the side of participants and monitored their performance during each session.

Figure 2.1: The layout of the experimental chamber during the study. Participants sat in the chair on the left, and the experimenter sat at the desk on the right side of the chamber.

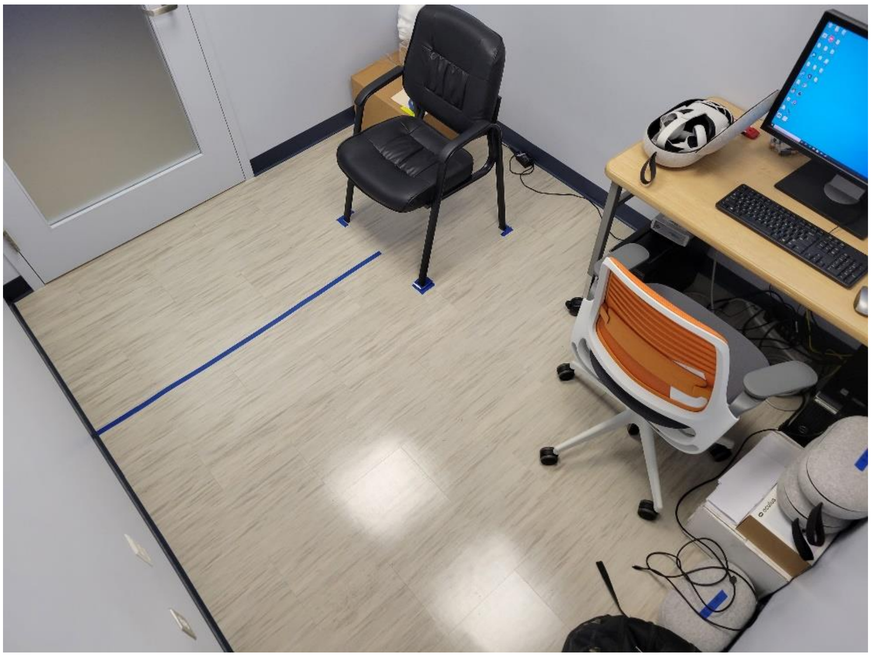
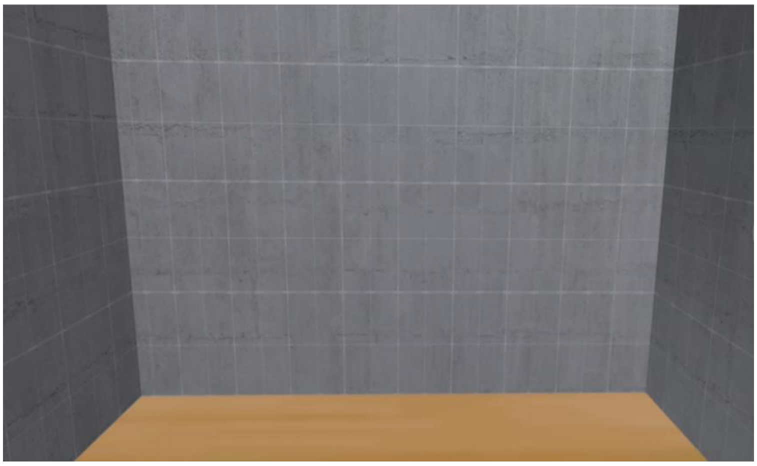


Figure 2.2: The virtual environment used in this study, viewed from the participant's perspective.



2.1.3 Virtual Environment

The experimental task took place in a simple virtual environment that consisted of a room with a wood textured floor and grey walls covered with a grid pattern (Figure 2.2). A light source positioned above participants illuminated the virtual room. This generated natural patterns of light and shadow on target objects that appeared in the room, based on their position relative to the light source. It also caused each target to cast a shadow onto the floor of the virtual room. These visual patterns and the texture gradients on the floor and walls were included to provide sufficient depth information for participants to adequately localize targets in this environment.

2.1.4 Setup

The procedures for this experiment were approved by the Institutional Review Board for the Social and Behavioral Sciences at the University of Virginia (IRB-SBS #4369). At the beginning of each experimental session, participants provided informed consent and completed a survey assessing basic demographic characteristics, including age, sex, and the extent of their previous experience with VR. Participants also completed the Edinburgh Handedness Inventory [138], which assessed their degree of preference for using their left compared to their right hand in everyday tasks. We measured participants' inter-pupillary distance (IPD) when focused at optical infinity using a medical grade pupillometer (Essilor Instruments, Model X81705), and we used this measurement to adjust the IPD of the VR headset to one of the three possible settings using the sizing guidance provided by Meta (Table 2.1 below). Finally, the participant was introduced to the Oculus Quest headset, and the experimenter adjusted the headset straps until the headset was securely fastened to the participant's head and the participant reported having a clear view of the virtual environment.

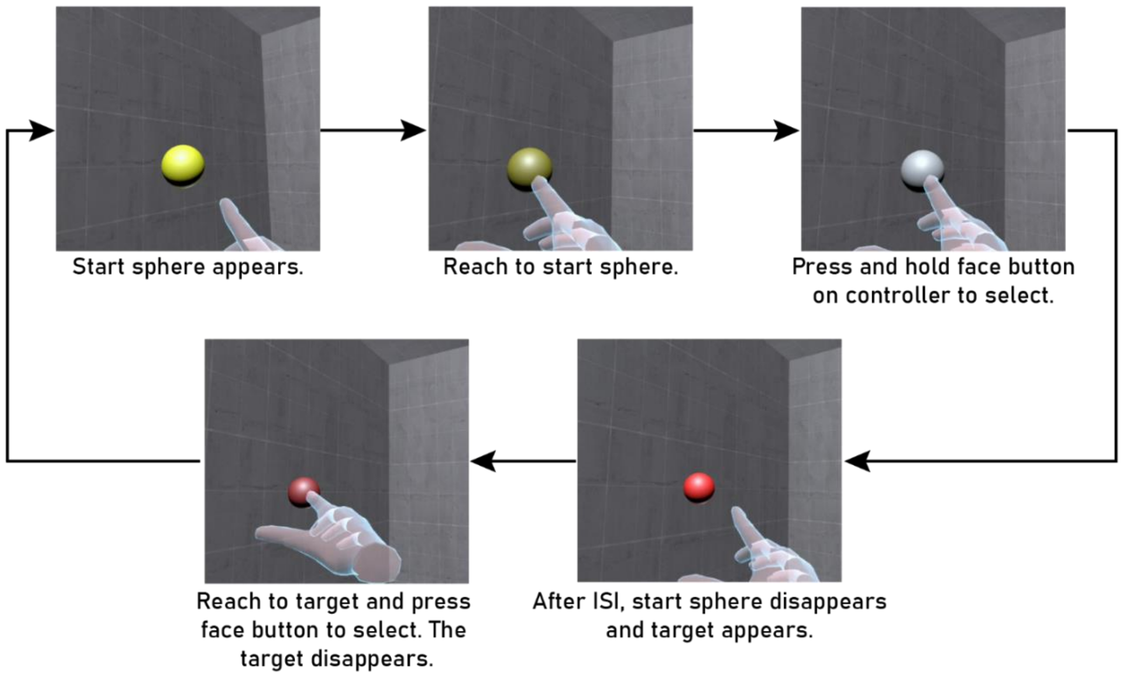
Table 2.1: The sizing guidance provided by Meta, which was used to determine the headset IPD value used for each participant.

Participant IPD	Headset Lens Spacing Setting
<= 61mm	1 (58mm)
61mm – 66mm	2 (63mm)
>= 66mm	3 (68mm)

2.1.5 Experimental Task

The experimental task was a discrete virtual hand reaching task in which participants used a virtual hand mapped to the movement of their handheld controllers to reach to targets at different locations in 3D space (Figure 2.3). Before the beginning of each trial, a yellow "start" sphere appeared at a specified position in the environment. Participants began each trial by moving their virtual hand until the tip of their index finger touched the yellow start sphere. When this occurred, the color of the sphere darkened to indicate that it could now be selected. Participants then pressed a specified button on the controller ("A" button for right hand movements, and "X" button for left) to select the start sphere while keeping their fingertip inside the start sphere, and the start sphere turned grey to indicate a successful selection. After a random interval (min = 0.5s, max = 1.5s), if the virtual fingertip had not yet left the start sphere, then the start sphere disappeared and a red "target sphere" appeared somewhere in the environment. Participants then moved their virtual hand to select the target sphere. When the fingertip of the virtual hand touched the target sphere, the sphere's color darkened to indicate that it could be selected. Participants then pressed the appropriate button on the controller to select the target sphere. When a target sphere was selected it disappeared, and the start sphere reappeared to allow participants to begin the next trial.

Figure 2.3: The sequence of events in the discrete reaching task used in the current study.



Participants were instructed to select each target sphere "as quickly and accurately as possible" and only to press the button to select a target once they were sure that they had reached the target. These instructions were designed to elicit movements that reflect the constraints of typical virtual hand reaching movements, in which participants must accurately specify both the direction and extent of the movement (e.g., [39,115,176]). The variable fore-period between the selection of the start sphere and the appearance of the target sphere was included to ensure that all movements began with the hand stationary at the starting location. To minimize any effects of fatigue, participants were instructed to rest as needed between trials and took mandatory five-minute rest breaks between experimental sessions.

The position and size of objects were defined using Unity units (1 unit ≈ 1 meter). All the spheres in this study were 0.05 units in diameter. Start spheres could either appear 0.25 units to the left of the participant's body midline, or 0.25 units to the right of the body midline. In both conditions, start spheres were positioned 0.25 units away from participants along the depth axis and at participants' eye level, which was fixed at 1.00 units above the virtual floor (Figure 2.4). Targets could appear 0.2 units away from their associated start sphere in one of five different directions (i.e., "up", "down", "left", "right", "away"; Figure 2.5a-b). These same locations were used to position targets relative to both potential start sphere locations, resulting in the full set of potential target locations shown in Figure 2.5c. An additional set of 12 other target locations involving different movement distances were also included in this study, and movements to these targets will be explored in future work. Focusing on the subset of 5 equidistant targets described above allowed us to explore how users adapt their reaching behaviors as a function of movement direction when movement distance is held constant.

Figure 2.4: The two potential start sphere locations in the current study. Distances are in Unity units.

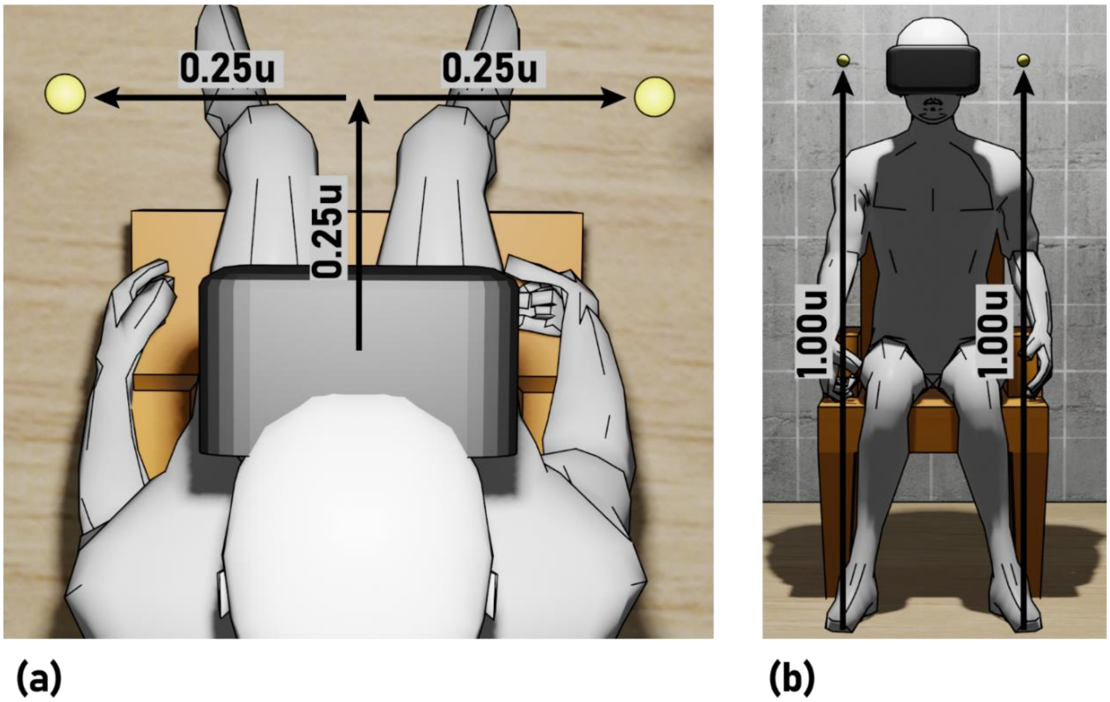
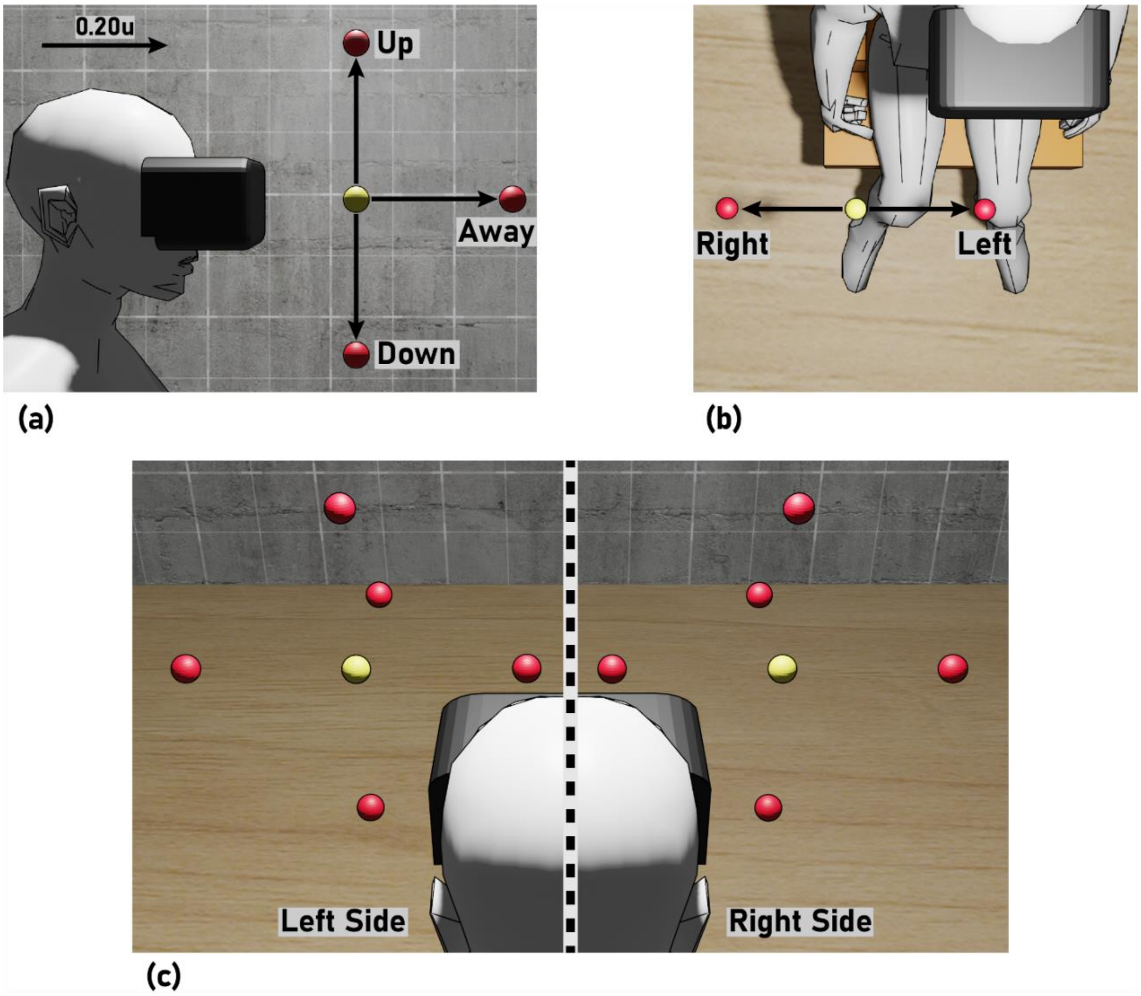


Figure 2.5: Elements (a) and (b) show how targets were positioned relative to each start sphere, using the start sphere in the right hemispace as an example. Element (c) shows the full set of potential target locations for each of the two starting position spheres



2.1.6 Procedure

The experiment consisted of an introduction to the task followed by four experimental sessions. At the beginning of each session, the experimenter calibrated the VR headset to ensure that the location of targets relative to the participant would remain consistent across all participants and sessions. To accomplish this, the participant was instructed to sit straight up in the chair with their back against the back of the chair, their feet flat on the floor, and their arms resting on the armrests. The experimenter then visually aligned the headset with a reference line on the floor to ensure that the headset was positioned properly in the yaw axis (i.e., pointing straight ahead along the participant's body centerline), and used a level to ensure that the headset was level with the horizon along the pitch and roll axes. When the headset was positioned properly, the participant was instructed to press and hold a button on one of the handheld controllers to reset their view to their current head position.

At the beginning of the study, participants were introduced to the experimental task using a set of target locations that were not used during the experimental sessions. In this practice session, the start sphere was positioned directly in front of participants along their body midline, and targets appeared in the same set of potential movement directions relative to this unique start location. The experimenter walked participants through the experimental task step by step, and participants then practiced the task while the experimenter monitored and corrected any errors in following the procedure. Participants then completed four experimental sessions that each lasted approximately 10-15 minutes. Within each session, the location of the start sphere (i.e., the interaction hemispace; "left side", "right side") and the hand used to perform the reaching movements ("left hand", "right hand") remained constant. The levels of these two factors were crossed orthogonally to produce the four experimental sessions: left side/left hand, left side/right hand, right side/left hand, and right side/right hand. Session order was counterbalanced across participants using a Latin square design. The movement direction in each trial was randomized, with the constraint that each potential movement direction occurred 10 times in each session. Participants completed 170 trials in each of the four sessions, for a total of 680 trials per participant. Of these, 200 trials per participant involved movements to the target locations of interest in the present work (Figure 2.5c). This approach resulted in a 5 (*direction*; up, down, left, right, away) × 2 (*hand*; dominant right/non-dominant left) × 2 (*side*; left side, right side) repeated measures design.

2.2 Kinematic Analyses

2.2.1 Data Collection and Pre-Processing

The experimental software captured the *x*-, *y*-, and *z*-position of the virtual fingertip at a nominal sampling rate of 90 Hz, which corresponded with the specified refresh rate for the VR display in our experimental program. This refresh rate was selected because it minimized the number of missing frames in the data collected from our program, compared to higher potential refresh rates. The program also recorded other information useful for interpreting the results of kinematic analyses, including the number of button presses that occurred during each trial. The program exported the data for each session to a CSV file that was stored locally on the Oculus headset, and the files for each participant were extracted to a desktop computer for further analysis.

Missing position data were interpolated using spline interpolation, and the data were resampled to a constant 90 Hz sampling rate. The resampled data describing the x, y, and z position of the virtual fingertip over time were then filtered using a 2nd order Butterworth filter with settings appropriate for calculating each kinematic metric (i.e., half amplitude cutoff at 20 Hz for $SPARC$, and 8 Hz for all other metrics [11,79]).. Filtering the data at this early stage in the analysis reduced the risk of amplifying measurement noise by differentiating a noisy signal [79]. To minimize any potential influence of filter artefacts on kinematic data recorded during the first and last sessions, hand position was recorded for at least two seconds before the onset of the first trial and two seconds after the end of the last trial in each session.

The filtered finger position data were then used to calculate the cumulative Euclidean distance travelled by the participant's finger at each time point during the session, which was denoted as $d_{cumulative}(t)$. For clarity, the value of $d_{cumulative}$ for any given time point t was given as

$$d_{cumulative}(t) = \sum_{i=2}^{i_t} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 + (z_i - z_{i-1})^2}$$

where t is the time at the current measurement point, i_t is the index of the current measurement point in the dataset, (x_i, y_i, z_i) are the coordinates of the virtual finger at measurement point i, and $x_{i-1}, y_{i-1}, z_{i-1}$ are the coordinates of the hand at measurement point $i - 1$. Distances were calculated beginning at the second measurement point in each session ($i = 2$), using the first measurement point ($i = 1$) as a referent where it is assumed that $d_{cumulative} = 0$. This approach enabled us to combine three-dimensional hand coordinates into a single measure of distance traveled that was amenable to kinematic analysis. Importantly, this approach has been shown to perform significantly better than alternative approaches to combining 3D position data for kinematic analyses, such as measuring the distance of the hand from the starting point or separately differentiating position along each of the three axes and combining the results to yield one-dimensional velocity and acceleration profiles [79]. Finally, cumulative distance data from each filter configuration were differentiated using a center difference algorithm to calculate the velocity, acceleration, and jerk of the fingertip at each measurement point. These data were used to calculate each of the kinematic metrics of interest in the present work, using the procedures described below.

2.2.2 Calculating Kinematic Metrics

The first set of kinematic metrics, *peak velocity* (v_{peak}), *movement time* (MT), and *percent time to peak velocity* ($PTPV$), were calculated using relatively simple procedures. Table 2.2 below provides a detailed summary of the mathematical procedures that were used to derive each of these metrics from the pre-processed kinematic data. The second set of kinematic metrics ($PTPSE$ and d_{PSE}) were derived by parsing the velocity profile for each movement using a procedure similar to the one introduced by [36]. This approach used temporal and magnitude criteria applied to the velocity and acceleration profiles for each movement to identify the movement start, movement end, and the primary submovement endpoint. Although the specific threshold values used can vary situationally across different studies, the general structure of the parsing algorithm is relatively standard and well-defined. In the present work, the velocity profile for each movement was parsed using the following steps:

- Find the start time (t_{start}) and end time (t_{end}) for the movement. t_{start} is defined as the first time during the trial that the hand's velocity exceeds 2% of v_{peak}, and t_{end} is the last time during the trial that the hand's velocity falls below 2% of v_{peak}.
- Identify the time during the trial when the primary submovement endpoint occurs (t_{PSE}). Based on [36], the primary submovement endpoint was defined as the first instance after peak acceleration when either of the following two criteria were met:
    - *Re-acceleration*: A zero-line crossing from negative to positive acceleration coinciding with an increase in velocity, which features a relative maximum on the velocity profile that meets the following criteria:
        - The relative maximum reaches a magnitude of at least 10% of v_{peak}.
        - The peak of the relative maximum occurs at least 40 ms after the initial inflection

- *Braking*: A zero-line crossing from negative to positive jerk, which features a relative maximum on the acceleration profile that meets the following criteria:
    - The relative maximum reaches a magnitude of at least 10% of the maximum absolute acceleration achieved during the trial.
    - The peak of the relative maximum occurs at least 40 ms after the initial inflection.

With t_{PSE} identified for each movement, $PTPSE$ and d_{PSE} were then calculated using the formulas in Table 2.2. Finally, *spectral arc length* ($SPARC$), was calculated using the procedure described by Balasubramanian and colleagues [11,12], as implemented in a MATLAB function made available by those authors. Table 2.2 summarizes the precise mathematical procedures that were used to calculate this measure.

Table 2.2: The mathematical procedures used to calculate each of the kinematic metrics examined in the present work.

Metric Name	Calculation Procedure
Peak Velocity (v_{peak})	$v_{peak} \triangleq \max[v(t)]$ where $t_0 \leq t \leq t_1$, $v(t)$ is the velocity value at time t , t_0 is the time associated with the first measurement point containing data from the current trial, and t_1 is the time associated with the final measurement point containing data from the current trial.

Movement Time (MT)	$$MT \triangleq t_{end} - t_{start}$$ where t_{start} is the first time (in milliseconds) during the trial where $v(t) > 0.02 \times v_{peak}$ and t_{end} is the last time during the trial where $v(t) > 0.02 \times v_{peak}$ [131].
Percent Time to Peak Velocity ($PTPV$)	$$PTPV \triangleq \left(\frac{\text{argmax}\,[v(t)] - t_{start}}{MT}\right) \times 100$$ where $t_0 \leq t \leq t_1$.
Percent Time to the Primary Submovement Endpoint ($PTPSE$)	$$PTPSE \triangleq \left(\frac{t_{PSE}}{MT}\right) \times 100$$ where MT is the movement time for the current movement.
Distance to Target at Primary Submovement Endpoint (d_{PSE})	$$d_{PSE} \triangleq \sqrt{(x_{target} - x_{PSE})^2 + (y_{target} - y_{PSE})^2 + (z_{target} - z_{PSE})^2}$$ where $(x_{target}, y_{target}, z_{target})$ are the spatial coordinates of the target for the current movement, and $(x_{PSE}, y_{PSE}, z_{PSE})$ are the coordinates of the user's hand when the primary submovement occurs (i.e., at t_{PSE}).

Spectral Arc Length ($SPARC$)	$SPARC \triangleq \int_0^{\omega_c} \left[\left(\frac{1}{\omega_c} \right)^2 + \left(\frac{d\hat{V}(\omega)}{d\omega} \right)^2 \right]^{\frac{1}{2}} d\omega$ where $V(\omega)$ is the Fourier magnitude spectrum of $v(t)$, $V(0)$ is the DC magnitude, $\hat{V}(\omega)$ is the magnitude spectrum normalized with respect to the DC magnitude using the following equation, $\hat{V}(\omega) = \frac{V(\omega)}{V(0)}$ and ω_c is a frequency cutoff that is selected dynamically using the following formula $\omega_c \triangleq \min\{\omega_c^{max}, \min\{\omega, \hat{V}(r) < \bar{V}\ \forall\, r > \omega\}\}$ in which $\bar{V}$ is a threshold setting that sets an upper limit on the normalized magnitude values of each frequency band above a given potential value of ω_c, and ω_c^{max} is an upper bound that denotes the maximum acceptable value for ω_c [12].

2.2.3 Statistical Analysis

Of the 4000 total trials, only two trials (0.05%) contained evidence of tracking loss, which appeared as a flatline in the velocity curve followed by impossibly large velocity values (>10 units/second) as the finger appeared to travel a large distance instantaneously when tracking resumed. In addition, 95 trials (2.4%) contained evidence of target selection errors, whereby participants either paused for a long time during the movement (i.e., movement time greater than 3 × IQR above the third quartile) or failed to select the target with their first reaching attempt (i.e., the button was pressed more than once during a trial). Movement data from these two sets of trials would not accurately reflect the kinematics of typical virtual hand reaching movements, so these trials were removed from the dataset and the remaining 3903 trials (97.6%) were submitted for further analysis.

To address our research questions, we used multilevel linear models (MLM; [104]) to examine the influence of movement direction (*direction*) on each kinematic variable, and to examine if hand used (*hand*) and interaction hemispace (*side*) moderate this relationship. All models were fitted using the lme4 package [13] in R version 4.0.5 [152], and parameter estimates were derived using full maximum likelihood estimation. The MLM for each dependent variable was constructed using the bottom-up procedure described by Hox and colleagues [86], which involved beginning with a null model containing only random intercepts and added fixed effects one at a time for *hand*, *side*, *direction*, and their associated two- and three-way interactions. Likelihood ratio tests on the model deviance were used to determine if adding each predictor led to a significant improvement in model fit. The logic of this approach is that if a given factor (e.g., *direction*) produces systematic variability in the kinematic metric under investigation, then a model that includes that factor as a predictor should provide a better fit to the observed values of that metric compared to a model that does not include that factor as a predictor.

We included all possible main effects and interactions involving both the primary independent variable of interest (*direction*) and the potential moderators (*hand*, *side*). However, a specific subset of these effects was most directly relevant to addressing our research questions. Namely, if users' movement kinematics changed as a function of movement direction (RQ 1), then we would expect to observe a significant main effect of *direction* in the MLM for one or more of the kinematic measures. If these *direction*-dependent kinematic changes emerged differently depending on the *hand* used to perform a movement or the *side* of the body where a movement occurred (RQ 2), then we would expect to observe significant two- or three-way interactions between *direction* and the moderating variables *hand* and *side*. Significant main effects and interactions were further explored using Bonferroni-corrected post-hoc comparisons. The goal of these comparisons was to address RQ 3 by quantifying *how* the kinematic properties of users' reaching movements changed as a function of *direction*, *hand*, and *side*.

Some effects (e.g., the main effects of *hand* and *side*, and the *hand* × *side* interaction) were not always of direct interest for addressing our research questions in the present study. However, they were included in the models to allow us to test for and interpret higher-order interactions with *direction*. Including these factors also allowed us to account for the possibility that for some metrics, these moderating variables may not interact with *direction* to influence a particular kinematic metric, but rather may exert an independent influence on those metrics that persists regardless of the direction in which a user moves. If these types of effects were present, then examining significant main effects of *hand* and *side* and the interaction between these two factors would allow us to further explore and quantify them.

Because this modeling approach involved performing 42 different likelihood ratio tests (7 per metric × 6 metrics), the familywise error rate (FWER) for this set of tests—the probability that any one effect could be observed entirely by chance—was likely well above the customary threshold of 0.05. To account for this, the p-values for these tests were adjusted using Holm's step-down procedure [85] to control the familywise error rate at 0.05. This procedure provides greater statistical power than a Bonferroni correction while still producing strong control over the FWER, which allowed us to be confident in the results of each individual likelihood ratio test. Furthermore, to ensure that the effects identified in the final model were not caused by a few unusual but highly influential observations, Cook's distance was calculated for each observation, and potential high-influence observations (Cook's $d > 4/n$) were further investigated. Where necessary, the final model was refitted without the high-influence observations to determine if this resulted in any substantive difference in the observed effects. In all cases, this resulted in no substantive changes to our results. Distributional assumptions for the final models were checked using normal Q-Q plots and plots of the residuals against predicted values, and any severe violations of these assumptions were noted. However, in the interest of interpretability, dependent variables were not transformed if violations of normality were detected. This decision was based on evidence from simulation studies indicating that parameter estimates from MLMs can be resilient to even significant violations of distributional assumptions [166].

2.3 Results

2.3.1 Overview

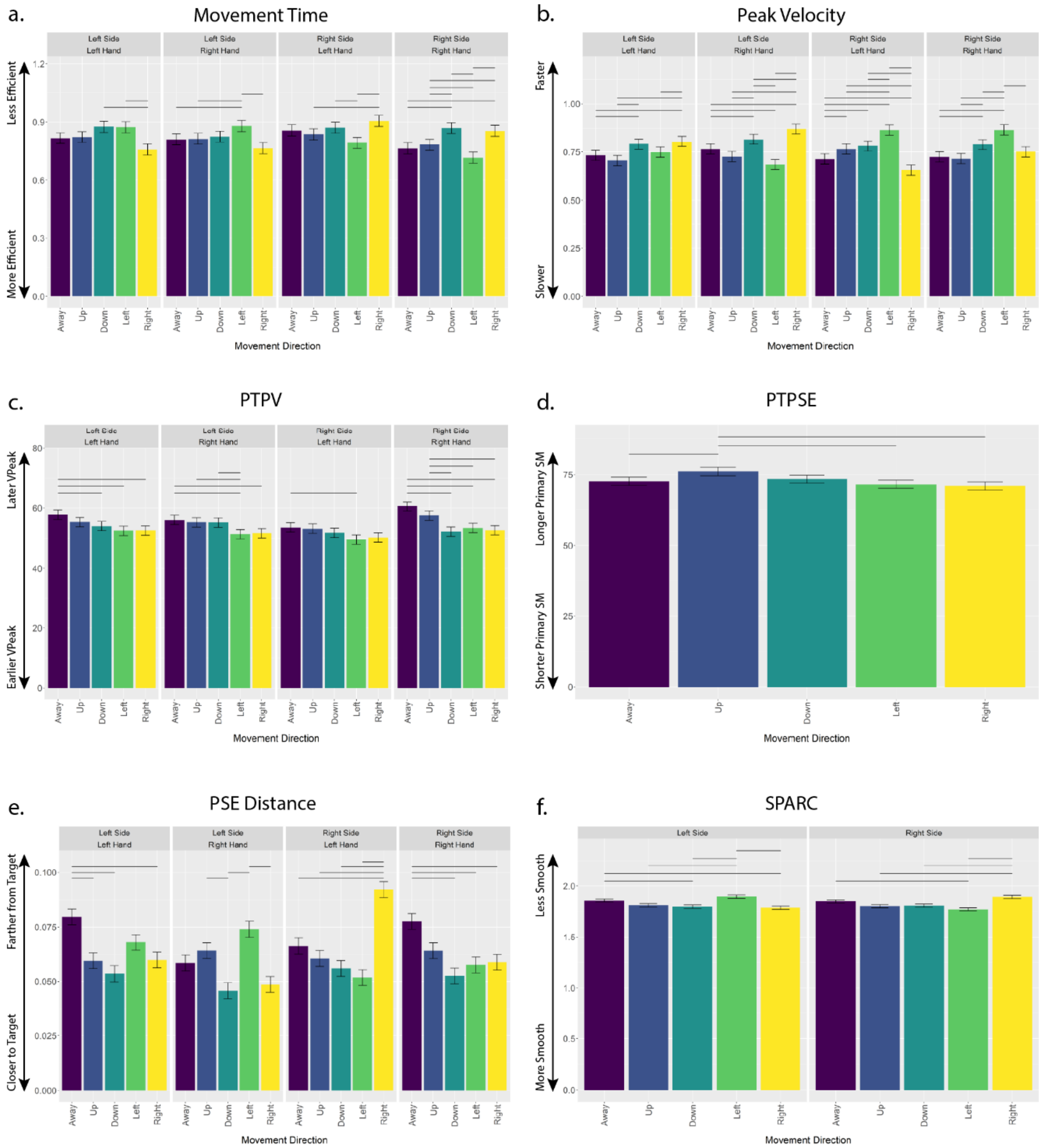
We observed significant main effects of *direction* on all the kinematic metrics we examined, indicating that MT, v_{peak}, $PTPV$, $PTPSE$, d_{PSE}, and $SPARC$ all varied significantly as a function of movement direction (Figure 2.6, column 3). This indicates that these properties of virtual hand reaches changed significantly when users reached in different movement directions (RQ 1). Furthermore, for every metric except $PTPSE$, there were also significant interaction effects between direction and the moderating variables *hand* and *side* (Figure 2.6, columns 5-7). This indicated that direction-dependent changes in these metrics emerged differently depending on the hand with which movements were performed and/or the side of the body on which movements occurred (RQ 2). Conversely, direction-dependent differences in $PTPSE$ did not emerge significantly differently as a function of hand or side, suggesting that direction-dependent changes in this property of users' reaches may have emerged similarly for reaches performed on either side of the body using the dominant and non-dominant arms. For $SPARC$, there was only a significant *side* × *direction* interaction (Figure 2.6, column 6, row 6). This indicated that $SPARC$ changed differently as a function of movement direction depending on the side of the body on which movements occurred, regardless of which hand was used to perform movements. Finally, for the metrics MT, v_{peak}, $PTPV$, and d_{PSE}, there were significant three-way interaction effects, indicating that these properties of users' reaches all varied differently as a function of movement direction depending on both the hand used to perform the movements and the side of the body on which movements occurred (Figure 2.6, column 7, rows 1-3, 5).

Figure 2.6: Summary of the Holm-corrected p-values from all likelihood ratio tests. The color in each cell indicates the extent to which each kinematic metric varied significantly as a function of each model factor.

2.3.2 Patterns of Kinematic Adaptation

Post-hoc comparisons revealed several patterns in how the kinematic properties of virtual hand reaches changed when users reached in different directions (RQ 3). Some of these patterns emerged similarly regardless of the hand used to perform movements or the side of the body where movements occurred, while others only emerged for specific combinations of *hand* and *side*. In the sections below, we summarize and discuss the most prominent of these patterns (i.e., those involving the largest differences in kinematic metric values). See Appendix A for the mean values of each metric across all combinations of *direction*, *hand*, and *side*. Figure 2.7 summarizes the results of post-hoc comparisons testing for significant differences between these means.

Figure 2.7: Marginal mean values for each kinematic metric, at the level of granularity justified by the results of likelihood ratio tests. Horizontal lines denote significant differences.



2.3.2.1 Kinematic Differences Between Inward and Outward Reaches

Most prominently, movements that involved reaching inward toward the body midline generally tended to exhibit more desirable kinematics (i.e., smaller MT and $SPARC$, and larger v_{peak}) than movements that involved reaching outward, away from the body midline. Specifically, when reaches occurred on the left side of the body, movements to the right (inward) exhibited significantly smaller MT and $SPARC$ and larger v_{peak} than movements to the left (outward). Conversely, when movements occurred on the right side of the body, these relationships were reversed. In this case, movements to the left (inward) exhibited significantly smaller MT and $SPARC$ and larger v_{peak} than movements to the right (outward). Together, these findings indicate that regardless of the hand with which users were moving, movements that involved reaching inward toward the body midline tended to be smoother ($SPARC$), faster (v_{peak},) and more efficient (MT) than movements that involved reaching outward (Figure 2.7a, b, and f).

Interestingly, there were also notable hand- and side-specific differences in the magnitude of the performance benefits for inward compared to outward movements. Namely, users exhibited significantly smaller d_{PSE} (i.e., ended their primary submovements closer to the target) when reaching inward than when reaching outward, but only when they were moving in the hemispace *contralateral* to their reaching arm. When reaches occurred on the left side of the body using the right hand, d_{PSE} was significantly smaller for movements to the right (inward) than for movements to the left (outward). Conversely, when reaches occurred on the right side of the body using the left hand, d_{PSE} was significantly smaller for movements to the left (inward) than for movements to the right (outward). The analogous differences did not reach significance when reaches occurred in the hemispace *ipsilateral* to the reaching arm (i.e., left side/left hand or right side/right hand), indicating that this pattern only emerged for reaches that occurred in the *contralateral* hemispace (Figure 2.7e). A similar pattern also emerged for v_{peak}, such that the v_{peak} benefit for inward compared to outward movements was noticeably larger for reaches that occurred in the *contralateral* hemispace than for reaches in the *ipsilateral* hemispace (Figure 2.7b). However, this benefit was still present for reaches in the *ipsilateral* hemispace. Together, this pattern of results suggests that outward reaches in the contralateral hemispace may have been particularly difficult to perform, such that users opted to move slower during their initial reaching attempts (smaller v_{peak}), end their primary submovements farther from the target (d_{PSE}), and perhaps rely more heavily on corrective submovements to close the remaining distance to the target.

2.3.2.2 Kinematic Differences Between Upward and Downward Reaches

There were also prominent kinematic differences between downward and upward reaches, and these differences tended to be localized to specific combinations of *hand* and *side*. For example, when users reached on the right side of their body using their right hand, downward reaches exhibited significantly larger MT and v_{peak} and significantly smaller $PTPV$ than upward reaches (Figure 2.7a-c). This indicates that in this condition, users tended to move faster during their initial movement (larger v_{peak}) when reaching downward than when reaching upward, but then spent a greater percentage of their movement time after peak velocity (smaller $PTPV$). This suggests that users may have been less accurate with their primary submovements when moving down than when moving up, and subsequently needed to rely more heavily on corrective submovements to successfully reach the target. Consistent with this notion, users also tended to end their primary submovements slightly farther from the target (larger d_{pse}) when reaching down than when reaching upward, although this difference did not reach statistical significance (Figure 2.7e). These additional corrections would take time to complete, possibly accounting for the fact that users took longer to complete their movements in this condition (longer MT) when reaching downward than when reaching upward (Figure 2.7a).

A slightly different pattern of differences emerged when users instead reached on the *left* side of their body using their *left* hand. In this condition, users still exhibited significantly larger v_{peak} when moving down than when moving up (Figure 2.7b). However, while MT and $PTPV$ values still trended slightly larger for downward reaches than for upward reaches, these differences fell short of statistical significance (Figure 2.7a and c). This suggests that downward reaches performed on the left side of the body using the left hand may exhibit kinematic patterns similar to those observed for downward reaches performed on the right side using the right hand, with primary submovements that are faster (v_{peak}) but less accurate and require users to rely more heavily on corrective submovements. However, in this case, these kinematic costs for downward compared to upward movements seem to have been smaller than those observed for reaches on the right side using the right hand. This could account for the fact that while users did tend to take slightly longer (larger MT) to reach downward than to reach upward in this condition, this difference fell short of statistical significance.

Finally, yet another unique pattern of differences emerged when users reached on the *left* side of their body using their *right* hand. In this case, downward reaches exhibited both significantly larger v_{peak} and significantly smaller d_{PSE} than upward reaches, with no corresponding significant difference in MT (Figure 2.7a, b, and e). This indicated that when users used their right hand to perform virtual hand reaches on the left side of their body, they were able to move faster during their initial reaches (larger v_{peak}) and end their primary submovements closer to the target (smaller d_{PSE}) when reaching downward than when reaching upward. While these kinematic differences did not result in a significant difference in the total time required to complete downward and upward movements (MT), they do suggest that downward reaches in this condition may have used a different strategy to achieve this same level of overall performance.

2.3.2.3 Reaches Away from Users in the Ipsilateral Hemispace

When users performed virtual hand reaches in the hemispace *ipsilateral* to their reaching arm (i.e., right side/right hand, or left side/left hand), we found that reaches in the away direction exhibited some unique kinematic properties. Namely, in these conditions, reaches in the away direction tended to exhibit the smallest v_{peak} and largest $PTPV$ values, while also exhibiting the largest d_{PSE} values. This indicates that when users reached away from themselves along the depth axis, while moving on the same side of their body as their reaching arm, their movements tended to involve relatively slow primary submovements (smaller v_{peak}; Figure 2.7b) that reached peak velocity later in the movement (larger $PTPV$; Figure 2.7c). Interestingly, although users tended to end these primary submovements particularly far from the target (large d_{PSE}; Figure 2.7e), they were still able to reach the target in a relatively short amount of time (small MT; Figure 2.7a). This pattern may reflect a movement strategy that users adopt to efficiently reach targets positioned at depth in a VR environment, whereby users opt to move slower during the early phases of movements and incorporate feedback-based corrections earlier in their reaches to compensate for initial ambiguity regarding the depth of a target in space.

2.3.2.4 Direction-Independent Effect of Hand on PTPSE

Finally, although we were primarily focused on the role of hand and hemispace as potential moderating variables, we also observed a case in which one of these variables exerted *direction*-independent effects on users' movement behaviors that emerged similarly for movements in all movement directions. Namely, when averaged across all levels of *side* and *direction*, users exhibited significantly larger $PTPSE$ when moving with their right hand than when moving with their left hand. This effect was not subsumed by any higher-order interactions, indicating that regardless of the direction in which users were moving or the side of the body on which a movement occurred, users ended their primary submovements later in the movement when they reached with their right hand than when they reached with their left hand. This points to a general performance benefit for reaches using the dominant hand, suggesting that movements with this hand may tend to rely less heavily on corrective submovements to successfully reach targets.

2.4 Intermediate Discussion

2.4.1 Summary of Findings

As the emerging concept of the metaverse fuels a growing interest in VR [46], and virtual hand reaching remains a prominent means of interacting with VR displays, it will be critically important to understand how users adapt their reaching movements during virtual hand interactions. Past work studying reaching movements in the physical world reveals that users often adapt various kinematic properties of their reaching movements when faced with differences in various properties of a reaching task, including movement direction, hand, and hemispace. However, to our knowledge, no work to-date has thoroughly examined how these three properties interact to influence users' reaching movements during virtual hand interactions. To address this gap, we had users perform virtual hand reaches in five different directions, on both sides of their bodies, using both their dominant and non-dominant hands. Kinematic analyses of users' movements revealed that users did adapt their virtual hand reaching movements when moving in different directions, and many of these adaptations emerged differently depending on the hand they used to perform movements (dominant, non-dominant) and/or the hemispace in which the movements occurred.

Each of the six kinematic metrics we examined changed as a function of movement direction (RQ 1), and for all but one metric the effect of movement direction was significantly moderated by hand dominance and/or interaction hemispace (RQ 2). Our analysis also revealed several prominent patterns in how users adapt these kinematic properties of their movements during virtual hand reaching (RQ 3). Most notably, users tended to exhibit "better" values on several kinematic measures (i.e., MT, v_{peak}, and $SPARC$) when they reached inward, toward their body midline than when they moved outward, away from their body midline. There were also notable kinematic differences between reaches in the upward and downward directions that emerged differently for different combinations of *hand* and *side*. When users reached on the right side of their body using their right hand, or on the left side of their body using their left hand, there were some kinematic costs associated with reaching downward compared to upward.

However, when users used their right hand to select targets on the left side of their body, downward reaches instead exhibited kinematic benefits compared to upward reaches. These and the other patterns of results we report above reveal how when users perform virtual hand reaches, both the level of movement performance they achieve and the strategies they use to achieve that performance can change as a function of movement direction, hand dominance, and the hemispace in which a movement occurs.

2.4.2 Comparison to Previous Results

By examining how movement direction, hand dominance, and hemispace jointly influence reaching movement kinematics, the present study examined reaching movements in conditions that have not yet been heavily studied in previous work (i.e., reaches in different directions that are performed entirely within the left or right hemispace, using the left or right hand). Consequently, it is challenging to draw direct comparisons between our results here and the findings of previous work, since by design the present work examined conditions that have yet to be broadly studied. However, there were still at least two notable cases in which our findings in the present study overlapped with results observed in past work.

First, recall that users exhibited significantly larger v_{peak} (indicating faster movements) when they reached in the down direction than when they reached upward, and this difference emerged for all but one combination of side and hand (i.e., right side/left hand). We also found that users ended their primary submovements significantly closer to the target (smaller d_{PSE}) when moving down than when moving up, but only for reaches on the left side using the right hand. These findings are consistent with patterns that have been found to emerge when users use their right hand to perform upward and downward virtual hand reaches from a starting position near the body midline [39], and suggest that these patterns can also emerge for reaches that do not begin near the body midline. However, like the findings of [39], these findings also run counter to the patterns observed for center-out reaches to physical targets, where users have instead been found to end their primary submovements *farther* from the target (larger d_{PSE}) when moving down than when moving up [25,113]. A subsequent analysis of the data from [39] suggested that this discrepancy may reflect a VR-specific movement strategy, whereby users move in a way that maximizes the availability of depth information from occlusion between their virtual hand and the target to inform their corrective submovements [40].

Second, recall that users tended to exhibit smaller MT (more efficient movements), smaller $SPARC$ (smoother movements) and larger v_{peak} (faster movements) when they reached inward, toward their body midline than when they reached outward, away from their body midline. These findings were consistent with the results of past work by Keulen and colleagues [97] (Experiment 2), who had users perform 3D reaches between physical targets at different locations in the coronal plane (i.e., on a touchscreen computer monitor). In this study, users began with their hand at a starting position that was either on the left or right side of their body midline, and they reached inward to select a target positioned at the body midline. Users performed these movements using either their left or right hand with and without visual distractors present (i.e., other non-target objects). The authors found that the right hand had the smallest MT (indicating more efficient movements) when users started on their right side and reached to the left (i.e., when reaching inward), while the left hand exhibited the smallest MT when users started on the left side and reaching to the right (i.e., reaching inward). Although the presence of distractor targets may have influenced the results, both Keulen et al. and the current study provide initial evidence to suggest that the smaller MT for inward vs. outward reaches that we observed here may also occur for reaches to real-world targets. However, since Keulen and colleagues did not examine v_{peak} and $SPARC$ in this study, the same cannot be said for these other kinematic properties.

2.4.3 Extending Past Findings for Virtual Hand Reaches

Past work examining the influence of movement direction, hand, and hemispace on reaching movement kinematics in VR has either focused on examining the effects of one of these factors in isolation [15,39,102,112], or has examined the joint effects of only two out of the three factors (i.e., movement direction and hand; [7]). Specifically, most of this past work has focused on examining the effects of movement direction on reaching kinematics during center-out reaches, in which the user begins with their hand positioned in the midsagittal plane (i.e., on the body midline) and reaches to select targets at different locations in 3D space [7,39,102,112]. For all but one of these studies (i.e., [7]), users performed reaches using only one of their hands. The present work expands on these results by revealing how movement direction, hand dominance, and hemispace all interact to influence the kinematic properties of virtual hand reaches. This provides a much more complete empirical account of how these three factors influence users’ arm movement kinematics during virtual hand reaching.

For past work that examined reaches in movement directions similar to those examined here (i.e., directly up, down, left, right, and away), our findings reveal how previous work showing the effect of movement direction on reaching kinematics may generalize from center-out reaches to reaches performed on either side of the user's body, using either the dominant or non-dominant hands. This specifically applies to past work from our laboratory [39], in which users began at a central starting position in the midsagittal plane and reached in six different movement directions to select virtual targets at different locations in 3D space. The task required users to reach primarily along the horizontal axis (directly to the left or right of the starting position), vertical axis (directly up or down), or depth axis (directly toward or away from the user). All the participants in this study were right-handed and performed the task using their dominant right arm. This past work reported three principal findings, which we consider in turn below.

First, this past work found that in this context, movement direction did not significantly influence MT. Our results here suggest that this finding may not generalize from center-out reaches to reaches performed in the left or right hemispace, using the left or right hand. Specifically, we found that for all four combinations of hand and hemispace, users exhibited significantly smaller MT when they reached in directions that involved moving inward (toward the body midline) than when they reached outward (away from the body midline). Together, these findings suggest that when users perform virtual hand reaches entirely on the left or right side of their body midline, there are significant MT benefits associated with reaching inward (to the right in the left hemispace, or to the left in the right hemispace) compared to reaching outward (to the left in the left hemispace, or to the right in the right hemispace. However, for center-out reaches that begin near the body midline, these hemispace-dependent effects of movement direction on MT may not be present. Rather, MT may be similar for reaches that involve moving to the left or right of a central starting position.

Second, the results of [39] indicated that users exhibited significantly larger v_{peak} and smaller d_{PSE} when reaching directly down than when reaching directly up. In the present study, we found that v_{peak} was also significantly smaller for downward reaches than for upward reaches for three out of the four combinations of hand and side. The sole exception was reaches performed on the right side using the left hand, where v_{peak} was not significantly different between downward and upward reaches. This suggests that the v_{peak} benefits for downward vs. upward movements that were observed for center-out reaches can also emerge for reaches in these other three conditions, but may not emerge for reaches performed on the right side of the body using the left hand. This may reflect differences between the hands concerning the movement strategies and control policies for which each hand is specialized (e.g., [162,163]), which might yield unique control patterns that only emerge when users reach on the right side of their body using their left hand. Similar to the findings of [39], we also found that d_{PSE} was significantly smaller for downward reaches than for upward reaches, but only when users were reaching on the left side of their body using their right hand. For reaches involving the other combinations of hand and side, this difference did not reach statistical significance. This suggests that the d_{PSE} benefits for downward compared to upward reaches may be unique to reaches that are (1) performed using the right hand, and (2) either occur near the body midline (i.e., [39]) or on the left side of the user's body (the present work). Although we cannot draw conclusions regarding precisely why these kinematic differences occur, the fact that they are localized to movements performed in a particular region of space using the right hand suggests that this pattern may reflect a control strategy that uniquely emerges when the dominant arm is tasked with performing downward or upward reaches in these regions of space (e.g. [179]).

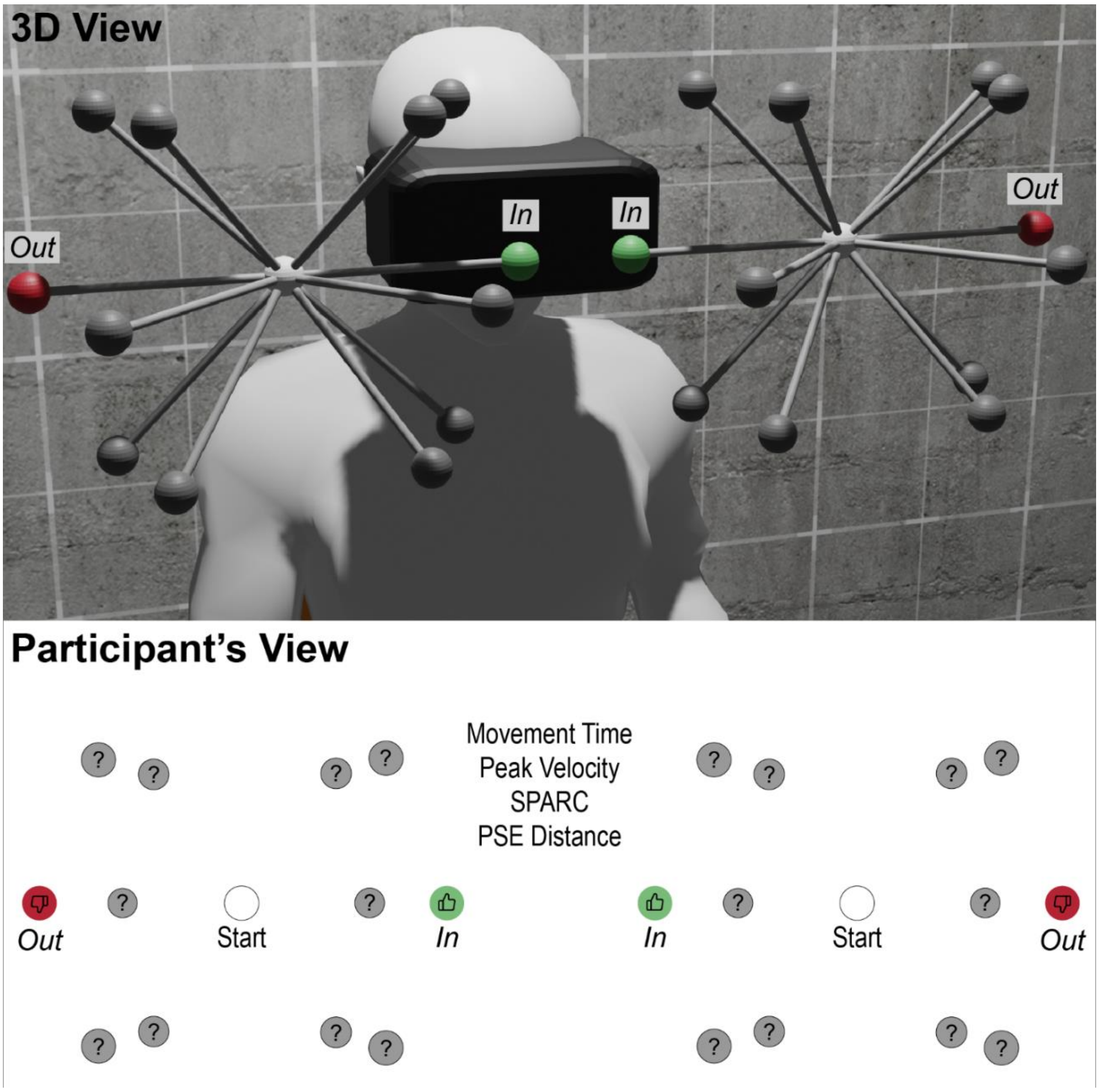
Finally, the results of [39] also revealed that users exhibited significantly larger v_{peak} and smaller d_{PSE} when reaching directly to the right than when reaching to the left. In the present work, we found that the tendency for users to exhibit larger v_{peak} for reaches to the right than for reaches to the left generalized from center-out reaches to reaches that were performed on the left side of the user's body using either hand. However, when users instead reached on the right side of their body, this pattern was reversed— v_{peak} was instead significantly larger for reaches to the left than for reaches to the right. This reflects our finding that v_{peak} was significantly larger for reaches that involved moving inward (toward the body midline) than for reaches that involved moving outward, away from the body midline. The results of [39] suggest that when users perform center-out reaches using their right hand, the pattern of v_{peak} differences between reaches in the left and right directions is similar to that observed for reaches that occur on the left side of the user's body. The results were similar for d_{PSE}. When users performed center-out reaches using their right hand [39] or reached on the left side of their body using their right hand (the present work), d_{PSE} was significantly smaller for movements to the right than for movements to the left. However, this pattern was reversed when users instead reached on the right side of their body using their left hand— d_{PSE} was significantly smaller for movements to the left than for movements to the right. Together, these findings suggest that when it comes to differences in v_{peak} and d_{PSE} between movements to the left and right of the starting position, center-out reaches [39] may behave similarly to reaches performed in the hemispace contralateral to the reaching arm (i.e., larger v_{peak} and smaller d_{PSE} for reaches to the right), while different patterns can emerge for reaches performed in the hemispace ipsilateral to the reaching arm. Although we cannot conclude precisely why this may occur, it is possible that the biomechanical constraints on users' movements, such as their initial arm postures and the associated inertial resistance and gravitational torques on each limb segment [65,161], may be more similar for center-out reaches and reaches in the contralateral hemispace (e.g., on the left side using the right hand) than for reaches performed in the ipsilateral hemispace (e.g., on the right side using the right hand). This similarity may have allowed users to adopt similar movement strategies when moving near their body midline and when moving in the hemispace contralateral to their reaching arm.

3 STUDY 2: A DEEPER LOOK AT THE EFFECTS OF DIRECTION, HAND, AND HEMISPACE

The previous study (Chapter 2) focused on reaches that involved moving in five cardinal directions (i.e., up, down, left, right, and away). Examining reaches in these five directions revealed for the first time that movement direction influences the kinematic properties of virtual hand reaches differently depending on both the hand used to perform movements and the side of the body on which movements occurred. This approach also provided a high-level overview of how virtual hand reaching kinematics change as a function of movement direction when users reach on each side of their body using each hand. However, of course, users do not only reach in these five directions when they interact with VR displays. Rather, users may need to move in any number of potential directions that might fall between the cardinal directions we examined in previous work. As such, it would also be useful to understand if and how the kinematic properties of virtual hand reaches change when users reach in movement directions other than the five that we examined in the previous work.

To begin to address this need, we performed a follow up study that incorporated a denser array of movement directions. Based on the results of the previous study, we focused on a range of reaching directions that either involved moving inward (toward the body midline) or outward (away from the body midline). Specifically, we examined reaches directly to the left or right of the starting location, but we also examined an additional set of 10 movement directions that all either involved moving inward (toward the body midline) or moving outward (away from the body midline; Figure 3.1).

Figure 3.1: The set of movement conditions examined in the present study, including two movement directions examined in the previous study (In and Out) and 10 additional movement directions that either involved moving inward or outward.



Including the *In* and *Out* directions from the previous study enabled us to examine if the largest effects we observed in Chapter 2 (i.e., differences in MT, v_{peak}, $SPARC$, and d_{PSE} between reaches in the *In* and *Out* directions) replicated with a different set of participants. Most importantly, however, including the 10 additional movement directions enabled us to provide a more fine-grained account of how reaching kinematics change as a function of movement direction across a denser range of movement directions. Since the metrics MT, v_{peak}, $SPARC$, and d_{PSE} were all significantly different between reaches directly *In* and reaches directly *Out* (Chapter 2), there was reason to suspect that these metrics might also vary across reaches in other directions that involve moving inward or outward. As such, we chose to focus the present investigation on understanding how these kinematic properties of virtual hand reaches change across this denser array of movement directions (Figure 3.1). We addressed the same research questions as in Chapter 2, but for this new set of movement directions:

1. Do the kinematic properties of users' virtual hand reaching movements change when they reach in different *movement directions*?
2. Do some *direction*-dependent adaptations in users' reaching kinematics emerge differently depending on which *hand* is used to perform movements and/or the *hemispace* in which movements occur?
3. How do the kinematic properties of virtual hand reaching movements change when users encounter different values of these three task properties?

3.1 Key Related Work

To our knowledge, no studies to-date have yet examined how the kinematic properties of virtual hand reaches change when users reach in this particular set of movement directions (RQ 1). As such, it is also not yet clear if and how any differences in reaching kinematics between these directions may emerge differently depending on the hand used to perform movements or the side of the body on which movements occur (RQ 2). Indeed, these questions have not yet been explored for goal-directed reaches performed to physical targets, either. As a result, there is relatively little past work from which to speculate as to how users may adapt the kinematic properties of their virtual hand reaches in the conditions we examined here.

However, some of the past work summarized in Section 1.5.1 provides some hints as to how users might behave in the reaching conditions we examined here. The relevant subset of work focused on center-out reaching tasks, in which users began with their hand positioned somewhere in the midsagittal plane (i.e., near the body midline) and perform goal-directed reaches that involve reaching away from their body to select targets at different locations in 3D space. Most of this work has focused on reaches to physical targets, but a few studies have also examined the kinematic properties of center-out reaches performed in VR. While this work focused on reaches that began near the body midline, rather than reaches that began on either the left or right side of the user's body, a few of these studies have examined reaches in movement directions that are similar to those we examined in the present work. As such, the results of these studies may provide a few hints as to the effects we might observe in the present work.

First, there is evidence that during center-out reaches performed in VR, users can exhibit larger MT [112] and smaller v_{peak} [102] when they reach in directions that involve moving *away from their body and downward*, compared to directions that involve moving *away from their body and upward*. The former pattern reached statistical significance in the original work, while the latter result reflects a trend that is observable in the results but was not examined statistically in the original work. Interestingly, slightly different results have been found when users perform center-out reaches to physical targets. Specifically, there is evidence that during 3D reaches to physical targets, users can instead exhibit smaller MT when they reach away and downward than when they reach away and upward [34,128]. These conflicting findings could be taken to suggest that users adapt their movements differently during real-world and virtual hand pointing, but they may also be related to differences between the tasks used in these studies. Specifically, the lowest targets in [112] were near or below waist height, while the lowest targets in the other studies were positioned higher up in the coronal plane. In any case, these findings do suggest that there may be significant differences in MT and v_{peak} between reaches in directions that involve moving *away from the body and upward* and directions that involve moving *away from the body and downward*.

There is also evidence that when users use their right arm to perform center-out reaches that involve moving *away from their body and to the right*, they tend to exhibit smaller MT[6,22,32,75,100,173] and larger v_{peak} [6,22,173,187,193] than when they move away and to the *left*. However, when users perform similar center-out reaches using their left arm, these patterns may reverse. Specifically, there is evidence that for center-out reaches using the left hand, users can exhibit larger v_{peak} [187,193] when they reach *away from their body and to the left* than when they reach *away from their body and to the right*. Together, these findings suggest that there may be MT and v_{peak} benefits associated with reaching away from the body and *toward* the side of the reaching arm (i.e., to the right with the right arm, or to the left with the left arm), compared to reaching away from the body and *away from* the side of the reaching arm (i.e., to the left with the right arm, or to the right with the left arm). However, it is important to note that these findings were all observed during reaching tasks with constraints different from those involved in virtual hand reaching. This includes 3D reaches performed to physical targets [6,32,75,100,193], 2D reaches during which the hand could only move in the horizontal plane [22,187], and reaches performed without visual feedback of the hand [173]. Consequently, these patterns may or may not generalize to reaches in the conditions we examined here.

Finally, one other study examining center-out reaching movements performed in VR reveals a potential way that users may adapt their reaching kinematics when they reach in the movement directions we examine here. Specifically, in a study comparing the kinematic properties of 3D functional movements performed in the real world and VR (HTC Vive), Arlati and colleagues [7] had users perform reach-to-grasp movements using their dominant and non-dominant hands to targets positioned at different locations in the vertical plane. The targets were items on either a virtual or physical grocery store shelf, and users stood in front of the shelf and reached to select the items using either their empty hand or a handheld VR controller. Targets could appear in nine different locations in a three-by-three array, with the items arranged on three shelves (rows) with three items positioned on each shelf (one in each of the three columns). Although this study was framed as a reach-to-grasp task, the VR version of the task approximated a virtual hand reaching task. In this context, they found that *peak velocity* (v_{peak}) during the reaching portion of the movements differed significantly as a function of movement direction. This reflected the fact that users exhibited significantly larger v_{peak} when they reached to the upper left target (i.e., reaching away from their body, up, and to the left) than when they reached to the middle-left target (i.e., reaching away from their body and to the left). They also found that when users reached to the lower left target (i.e., reaching away from their body, downward, and to the left), they exhibited larger MT and smaller v_{peak} when they reached using their non-dominant hand than when they reached using their dominant hand. This suggests that, at least for center-out reaches, reaches using the non-dominant arm may exhibit less desirable kinematic properties than reaches using the dominant arm when users move in this particular movement direction.

Together, past work examining center-out reaches highlights several ways that users may adapt the kinematic properties of their virtual hand reaches in the movement conditions that we examined here. However, it is not yet clear if any of these patterns may also emerge when users perform reaches that occur entirely on the left or right sides of their body. It is also not yet clear if these patterns may emerge differently when users reach using their dominant or non-dominant arms. Finally, most of the work to-date has focused on a much smaller subset of the movement directions we examined here. Consequently, for some of the movement directions we examined, the kinematic properties of reaches in these directions have not yet been previously explored, even in the context of center-out reaches. In short, from the results of past work, it is not yet clear how users adapt the kinematic properties of their virtual hand reaches when they reach in these different directions (RQ 1), or how these patterns may emerge differently depending on the hand used to perform movements and/or the side of the body on which the movements occur (RQ 2).

3.2 Methods

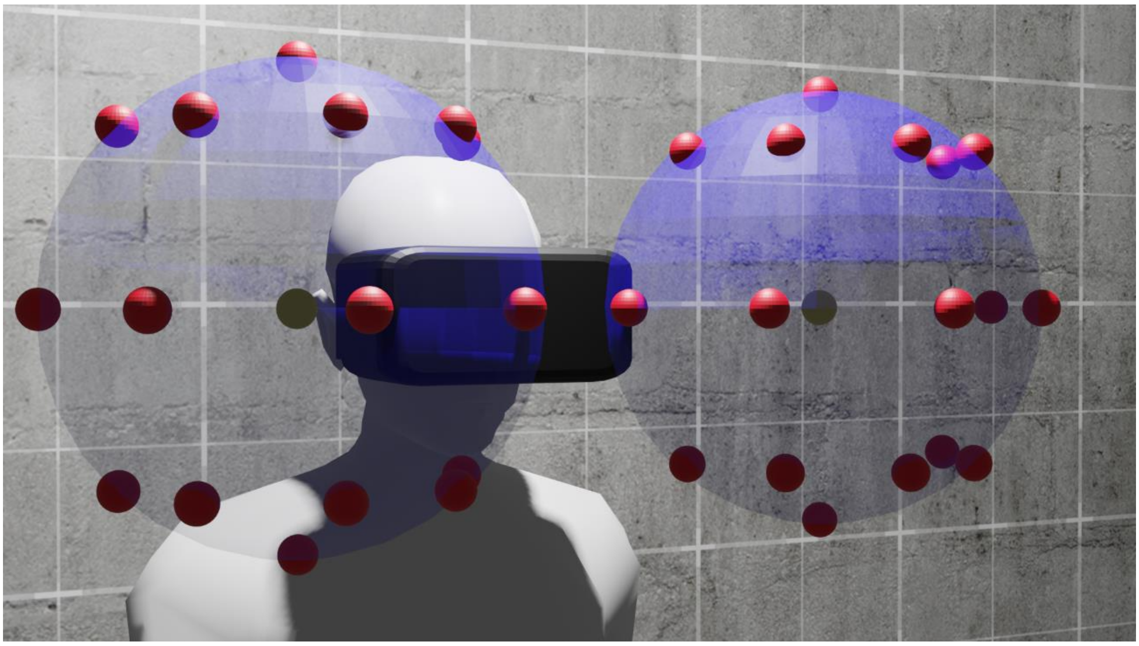
3.2.1 Participants

This study included a new set of 20 participants who did not participate in the previous study. Participants were recruited from the undergraduate, graduate student, and employee population at the University of Virginia (8 female, mean age = 25.7, range = 19-44). All participants had normal or corrected-to-normal vision and reported having no ailments that impacted their arm mobility. All participants expressed a strong right-hand preference, with scores greater than 40 (M = 84.89, SD = 15.7) on the Edinburgh Handedness Inventory (Oldfield, 1971). Eight participants reported having had some previous experience with the Oculus Quest or another consumer VR headset, while the remaining participants reported having no previous experience with VR.

3.2.2 Experimental Task

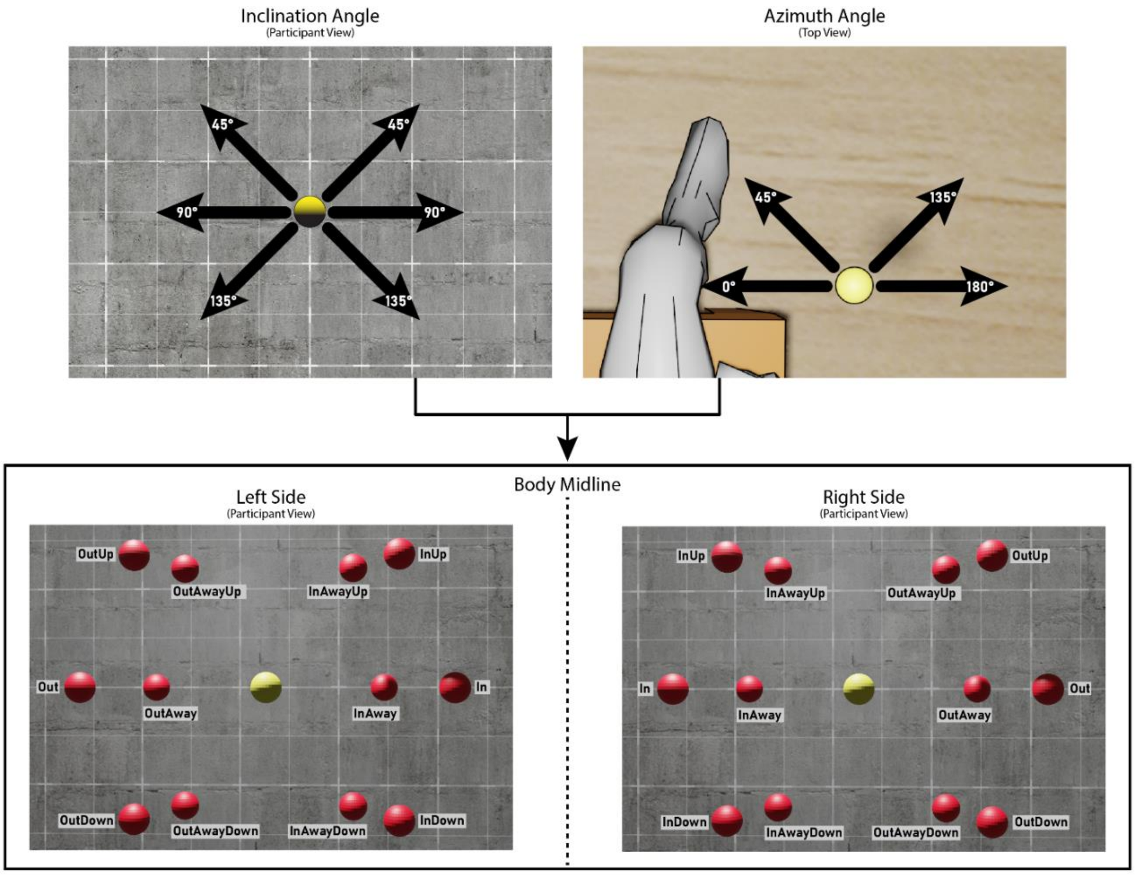
The task and experimental procedures in the present study were largely the same as in Chapter 2, with one exception. Namely, in the present study, targets could appear in a total of 17 different movement directions (Figure 3.2). All targets were positioned 0.20 units away from their associated start sphere. This arrangement produced a set of targets that were equidistant from their respective start spheres and evenly spaced out along an imaginary hemisphere that was centered on the start sphere (Figure 3.2).

Figure 3.2: The full set of target locations examined in the present task, showing how targets were equally spaced out and equidistant from the start sphere.



For the present study, we focused on the set of 12 movement directions that were derived by orthogonally combining four different azimuth angles with three different incline angles (Figure 3.3). Focusing on these 12 movement directions enabled us to examine a broader set of movement directions than in Chapter 2 while still benefiting from the flexibility of modeling movement direction as a factor (in this case, a 12-level factor). This was particularly important for this exploratory study, since treating movement direction as a factor allowed us to detect how each kinematic metric differed across the 12 movement directions without needing to make assumptions about the nature of these differences. Comparatively, potential alternative approaches such as modeling movement direction using semi-continuous linear effects of inclination and azimuth angles would have required us to make assumptions about how each kinematic metric varies as a function of movement direction (e.g., that each kinematic metric changes linearly as a function of inclination angle or azimuth angle). However, the increased flexibility that comes with modeling *n* movement directions as an *n*-level factor also comes with some tradeoffs, in that this approach places practical limits on the number of movement directions that can be examined in any one study. This is because fitting main effects and two- and three-way interactions for factors with many levels quickly consumes degrees of freedom in a model, and this can lead to convergence issues and overfitting if too many movement directions are examined. Given the size of our dataset in the present study, focusing on 12 movement directions enabled us to provide a much more fine-grained account of the relationship between movement direction and reaching kinematics while avoiding the overfitting and model convergence issues that could result from examining an even larger number of movement directions.

Figure 3.3: Visual summary of the set of the 12 movement directions examined in the present study. This set of directions was obtained by orthogonally combining the three incline angles pictured in the top left (45, 90, and 135) with the four azimuth angles pictured in the top right (0, 45, 135, and 180).



3.2.3 Procedures

As in the previous study, participants were introduced to the experimental task using a set of target locations that were not used during the experimental sessions. Participants then completed four experimental sessions. Within each session, the location of the start sphere (i.e., the interaction hemispace; “left side”, “right side”) and the hand used to perform the reaching movements (“left hand”, “right hand”) remained constant. The levels of these two factors were crossed orthogonally to produce the four experimental sessions: left hand/left side, left hand/right side, right hand/left side, and right hand/right side. Session order was counterbalanced across participants using a Latin square design.

The movement direction in each trial was randomized, with the constraint that each potential movement direction occurred 10 times in each session. This resulted in a total of 480 trials per participant, and a 12 (direction) × 2 (hand; dominant right/non-dominant left) × 2 (side; left side, right side) repeated measures design.

3.2.4 Statistical Analysis

Kinematic metrics were calculated using the same procedures used in Chapter 2. Of the 9,600 total trials, no trials were found to contain tracking loss. There was evidence of target selection errors in 389 trials (4%), whereby participants either paused for a long time during the movement (i.e., movement time greater than 3 × IQR above the third quartile) or failed to select the target with their first reaching attempt (i.e., the button was pressed more than once during a trial). Movement data from these trials would not accurately reflect the kinematics of typical virtual hand reaching movements, so they were removed from the dataset and the remaining 9,211 trials (96%) were submitted for further analysis.

To address our research questions in the present work, we used separate multilevel linear models (MLM; [104]) to examine the effects of *movement direction* (12 levels; Figure 3.3), *hand* (dominant right, non-dominant left), and *side* (left, right) on each of the four kinematic metrics. As in the previous study, all models were fitted using the lme4 package (Bates et al., 2015) in R version 4.0.5 (R Core Team, 2021), and parameter estimates were derived using full maximum likelihood estimation. The MLM for each dependent variable was constructed using the bottom-up procedure described by [86], which involved beginning with a null model containing only random intercepts and adding fixed effects one at a time for *direction, hand, side*, and their associated two- and three-way interactions. Likelihood ratio tests on the model deviance were used to determine if adding each predictor led to a significant improvement in model fit. The *p*-values for these tests were adjusted using Holm's step-down procedure [85] to control the familywise error rate at 0.05, correcting for multiple comparisons. Significant effects were then further explored using post-hoc comparisons. *P*-values for these comparisons were corrected using the Tukey adjustment.

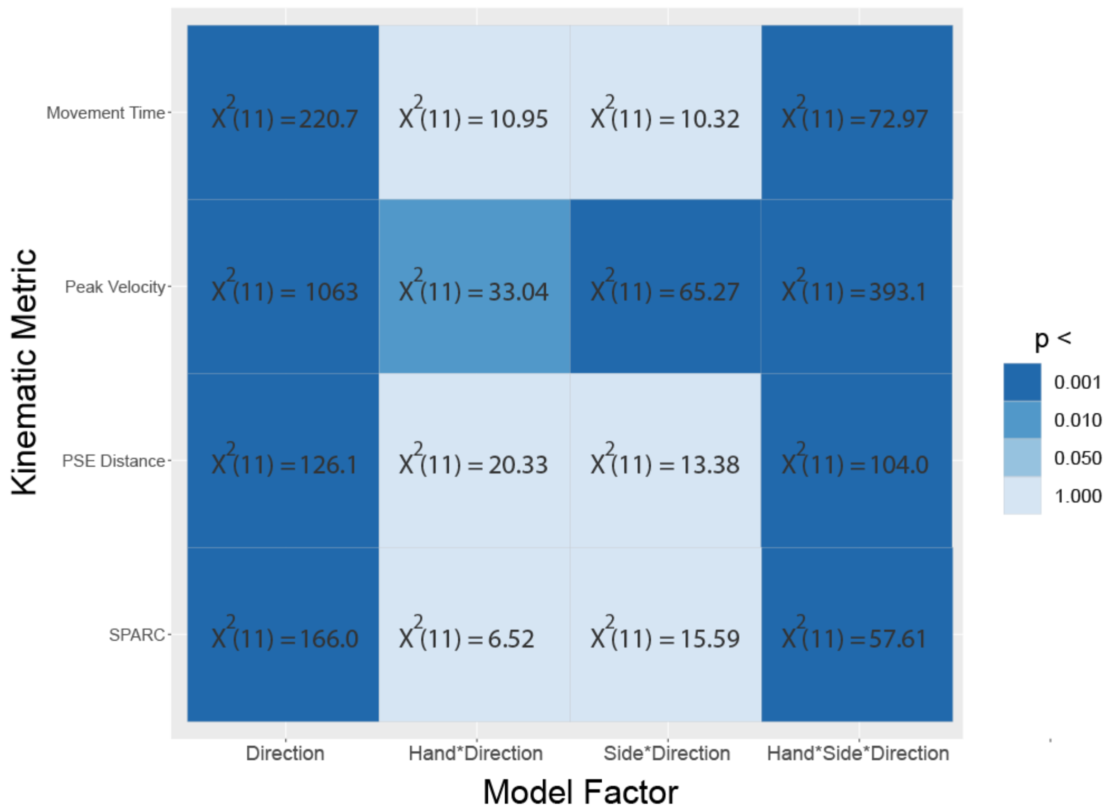
As in Chapter 2, to ensure that the effects identified in the final model were not caused by a few unusual but highly influential observations, Cook's distance was calculated for each observation and potential high-influence observations were further investigated. Where necessary, the final model was refitted without the high-influence observations to determine if this resulted in any substantive difference in the observed effects. In all cases, this resulted in no substantive changes to our results. Distributional assumptions for the final models were checked using normal Q-Q plots and plots of the residuals vs. predicted values, and any severe violations of these assumptions were noted. However, in the interest of interpretability, dependent variables were not transformed when violations of normality were detected. This decision was based on evidence from simulation studies indicating that parameter estimates from MLMs can be resilient to even significant violations of distributional assumptions [166].

Recall that we were first interested in understanding if users adapt the kinematic properties of their reaching movements when they reach in the 12 different movement directions (RQ1). If a particular kinematic property (e.g., *MT*) changed as a function of movement direction, then we would expect to see a significant main effect of *direction* for that property. This would indicate that, when averaged across all combinations of *hand* and *side*, the kinematic property in question changed significantly when users reached in different directions. If these effects emerged differently depending on the hand used to perform movements or the side of the body on which movements occurred (RQ2), then we would expect to see significant two-way interactions for *hand* × *direction* or *side* × *direction*. If these direction-dependent effects emerged differently as a function of both *hand* and *side*, then we would expect to see a significant *hand* × *side* × *direction* interaction. Finally, post-hoc comparisons enabled us to further explore how each kinematic property changed across the 12 movement directions we examined here, for each combination of *hand* and *side* (RQ 3).

3.3 Results

Figure 3.4 below summarizes the results of the likelihood ratio tests examining the effects of *direction*, *hand*, and *side* on each of the four kinematic metrics. A dotplot representing the values of each metric in each condition with confidence intervals is provided in Appendix B. A spatial view of how each metric changed as a function of movement direction is provided in Appendix C. A table containing precise values of each metric for each condition is included in Appendix D. In the sections below, we summarize our findings for each metric in turn.

Figure 3.4: Summary of the Holm-corrected p-values from all likelihood ratio tests. The color in each cell indicates the extent to which each kinematic metric varied significantly as a function of each model factor (i.e., the independent variables and their interactions).



3.3.1 Movement Time (*MT*)

There was a significant main effect of *direction* ($\chi^2(11)$ = 220.69, p < .001) on *MT* and a significant *hand* × *side* × *direction* interaction ($\chi^2(11)$ = 72.97, p < .001). This indicated that *MT* changed significantly as a function of movement direction, and that these *direction*-dependent differences in *MT* emerged differently depending on both the hand used to perform movements and the side of the body on which movements occurred (Figure 3.4). Post-hoc comparisons revealed that, as in Chapter 2, users tended to take less time to complete movements (smaller *MT*) when they reached directly *inward* than when they reached directly *outward*. This trend occurred for all four combinations of *hand* and *side*, but it fell short of statistical significance for one of the four conditions (i.e., Right Side / Left Hand). There were also significant differences in *MT* between reaches in the other movement directions, and these effects emerged differently for each combination of *hand* and *side*. We discuss each of these conditions in turn below.

3.3.1.1 Left Side, Left Hand

When users reached on the left side of their body using their left hand, MT was smallest for reaches directly *In*, largest for reaches in the *OutDown* direction, and assumed intermediate values for the remaining movement directions. Figure 3.5a-b summarizes how MT changed significantly as a function of movement direction for this combination of *hand* and *side*. Most notably, these results indicated that users took significantly less time to complete their movements (smaller MT) when they reached directly *In*, compared to reaches in (1) any of the six outward directions or (2) the *InAwayUp* direction (Figure 3.5a).

3.3.1.2 Left Side, Right Hand

When users reached on the left side of their body using their right hand, they tended to exhibit smaller MT for reaches in every inward direction except for *InDown*, and larger MT for reaches in every outward direction except for *OutAwayDown*. For this combination of *hand* and *side*, the 12 movement directions could therefore be conceptualized as falling into two general clusters with regards to MT. Specifically, MT was smaller for reaches in the *OutAwayDown* direction and for all but one inward direction (i.e., *InDown*), and large for reaches in the *InDown* direction and for all but one outward direction (i.e., *OutAwayDown*). The largest differences in MT between the movement directions in these two clusters reached statistical significance, as summarized in Figure 3.5c-e.

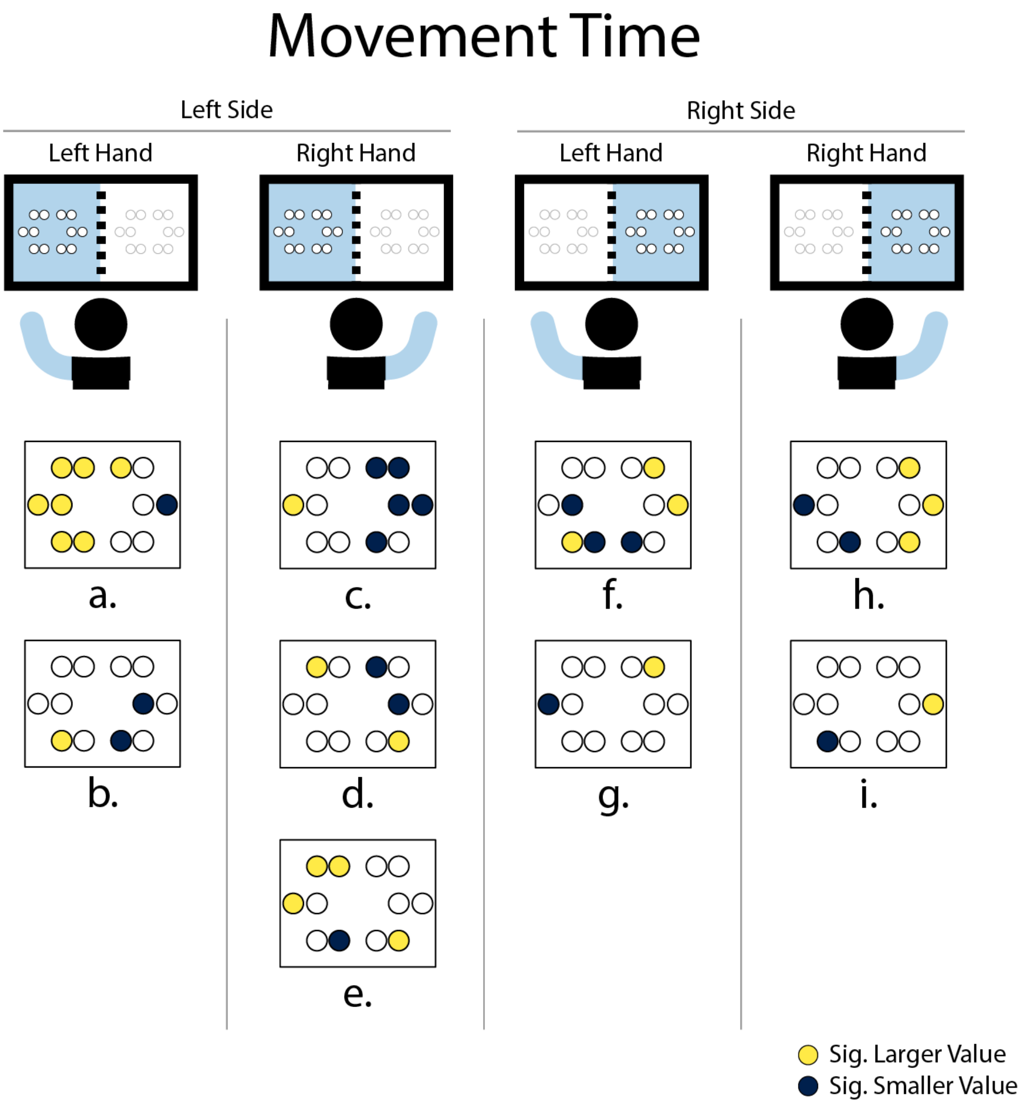
3.3.1.3 Right Side, Left Hand

When users instead reached on the right side of their body using their left hand, MT was largest for reaches in the *InDown*, *OutUp*, and *Out* directions, and smallest for reaches in the *InAway*, *InAwayDown*, and *OutAwayDown* directions. Post-hoc comparisons revealed that MT differed significantly between these two sets of movement directions (Figure 3.5f). Furthermore, although MT trended slightly larger for reaches directly *Out* than for reaches directly *In*, mirroring the findings of previous work (Chapter 2), this difference was not quite large enough to reach statistical significance. Figure 3.5f-g provide a full summary of the significant direction-dependent differences in MT that we observed for this combination of *hand* and *side*.

3.3.1.4 Right Side, Right Hand

Finally, when users reached on the right side of their body using their right hand, MT was smallest for reaches in the *In* and *InAwayDown* directions and largest for reaches in the *Out*, *OutDown*, and *OutUp* directions. Post-hoc comparisons revealed that *MT* was significantly different between these two sets of movement directions (Figure 3.5h). See Figure 3.5h-i for a full summary of how *MT* changed significantly as a function of movement direction for this combination of *hand* and *side*. We also noted that *MT* values in this condition appear to have been slightly lower than those observed for the other combinations of *hand* and *side*, particularly for reaches in the inward directions (Appendix C). This suggests that users took slightly less time to complete movements when reaching on the right side of their body using the right hand compared to the other combinations of *hand* and *side*, regardless of the direction in which they were moving.

Figure 3.5: A spatial view of how MT changed as a function of movement direction for each combination of hand and side. The movement directions of opposite colors (yellow vs. black) are significantly different from each other (Tukey-corrected p < .05).



3.3.2 Peak Velocity (v_{peak})

There was a significant main effect of *direction* on v_{peak} ($\chi^2(11) = 1063$, $p < .001$), and this effect was subsumed by significant two-way interactions for *hand* × *direction* ($\chi^2(11) = 30.04$, $p = .009$) and *side* × *direction* ($\chi^2(11) = 65.27$, $p < .001$). However, all these effects were subsumed by a significant three-way interaction involving all the factors ($\chi^2(11) = 393.12$, $p < .001$; Figure 3.6). This indicated that v_{peak} changed significantly as a function of movement direction in this task, and that these *direction*-dependent differences in v_{peak} emerged differently depending on both the hand used to perform movements and the side of the body on which movements occurred. Post-hoc comparisons confirmed the findings of Chapter 2 with respect to v_{peak}. Namely, for all four combinations of *hand* and *side*, users moved significantly faster (larger v_{peak}) when they reached directly *In* than when they reached directly *Out* (Figure 3.6). There were also significant differences in v_{peak} between reaches in the other inward and outward directions. As we observed for MT, these effects emerged differently depending on both the hand used to perform movements and the side of the body on which movements occurred (Figure 3.4). We discuss each of these conditions in turn below.

3.3.2.1 Left Side, Left Hand

When users reached on the left side of their body using their left hand, v_{peak} was largest (indicating faster movements) for reaches directly *In* and for reaches in directions that involved moving downward (i.e., *InDown*, *InAwayDown*, *OutDown*, *OutAwayDown*). Conversely, v_{peak} was smallest for reaches directly *Out* and for reaches in directions that involved moving upward (i.e., *InUp*, *InAwayUp*, *OutUp*, *OutAwayUp*). Post-hoc comparisons revealed that v_{peak} was significantly different between these two sets of movement directions (Figure 3.6a). v_{peak} was also significantly larger for reaches in the *OutAway* direction than for reaches in all four directions that involved moving upward (i.e., *InUp*, *InAwayUp*, *OutUp*, *OutAwayUp*; Figure 3.6b). A few other comparisons also reached statistical significance, as summarized in Figure 3.6c-d. However, the pattern described above reflected the most prominent direction-dependent differences in v_{peak} that emerged for reaches performed on the left side using the left hand.

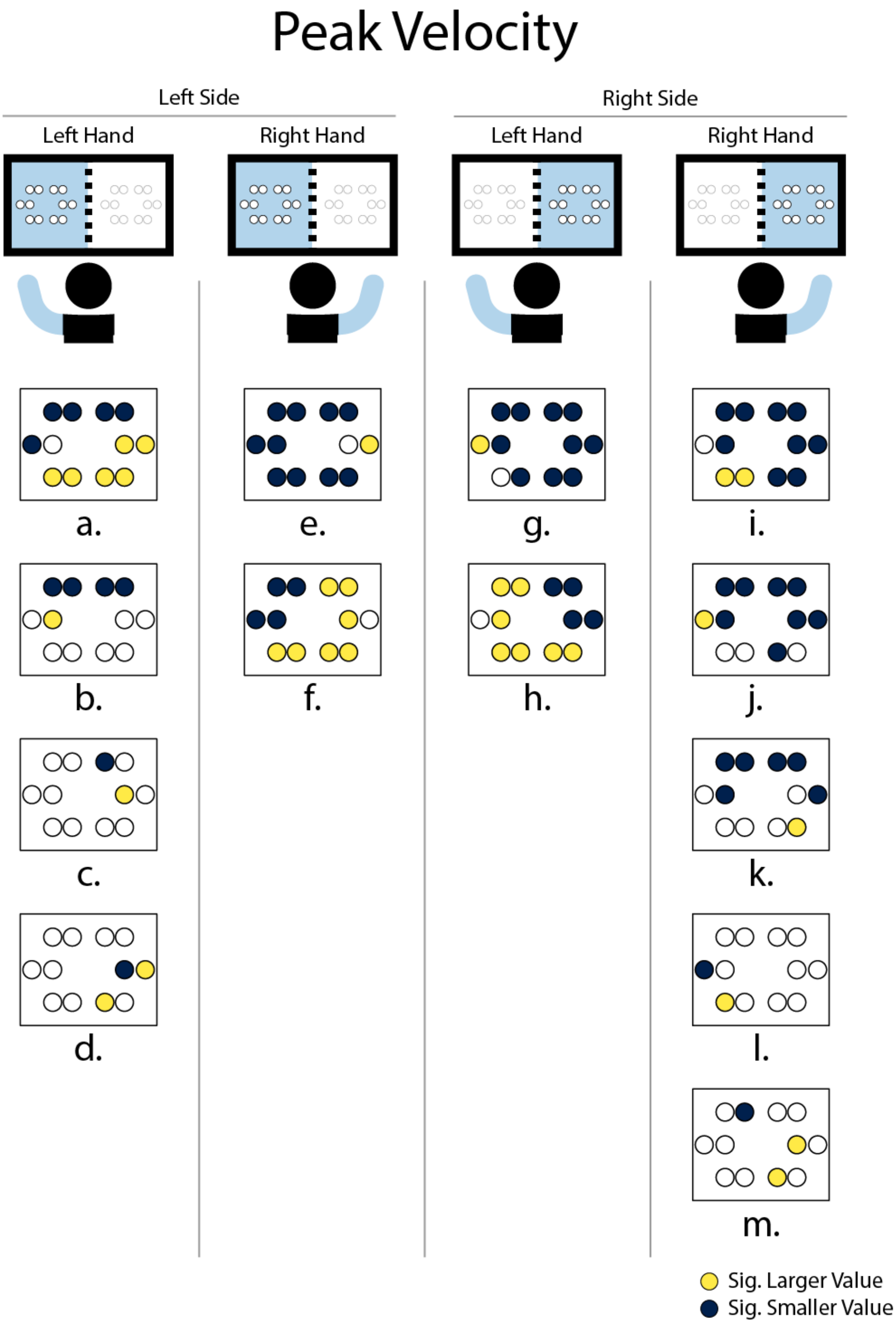
3.3.2.2 Reaches in the Hemispace Contralateral to the Reaching Arm

In the two conditions where movements occurred in the hemispace contralateral to the reaching arm (i.e., Left Side/Right Hand and Right Side/Left Hand), the relationships between movement direction and v_{peak} were nearly identical. Namely, v_{peak} was particularly small for reaches in the *Out*, *OutAway*, *OutUp*, and *OutAwayUp* directions. As a result, for reaches in the contralateral hemispace, v_{peak} was significantly smaller for reaches in these four directions than for reaches in all the eight remaining directions (Figure 3.6e-h). We also found that v_{peak} was particularly large for reaches in the *In* direction. As a result, v_{peak} was also significantly larger for reaches in the *In* direction than for reaches in 10 of the other 11 other directions (Figure 3.6e and Figure 3.6g). The direction for which this difference failed to reach significance was different for reaches on the left side using the right hand and reaches on the right side using the left hand, as summarized in Figure 3.6e and Figure 3.6g.

3.3.2.3 Right Side, Right Hand

Finally, when users reached on the right side of their body using their right hand, v_{peak} was largest for reaches in directions that involved moving both inward and down (i.e., *InDown* and *InAwayDown*), and was slightly smaller for reaches in the *In* direction. As a result, v_{peak} was significantly larger for reaches in the *InDown* and *InAwayDown* directions than for reaches in every other direction except for *In* (Figure 3.6i). v_{peak} was also significantly larger for reaches directly *In* than for reaches in every remaining movement direction except for *OutDown*, which exhibited slightly larger v_{peak} than all the other outward movement directions (Figure 3.6j). Users also exhibited significantly larger v_{peak} for reaches in the *InDown* direction than for reaches in the six movement directions where users exhibited the smallest v_{peak} values. This included reaches in the *Out* direction, reaches in the *InAway* direction, and reaches in all four directions that involved moving upward (i.e., *InUp*, *InAwayUp*, *OutUp*, *OutAwayUp*). This suggests that for reaches performed on the right side using the right hand, there were v_{peak} benefits associated with reaching in the *OutDown* direction, compared to these other six movement directions. A few other comparisons reached statistical significance, as summarized in Figure 3.6l and Figure 3.6m. However, the patterns described above reflect the most prominent direction-dependent differences in v_{peak} that emerged for reaches performed on the right side using the right hand.

Figure 3.6: A spatial view of how v_{peak} changed as a function of movement direction for each combination of hand and side. The movement directions of opposite colors (yellow vs. black) are significantly different from each other (Tukey-corrected p < .05).



3.3.3 Primary Submovement Distance (d_{PSE})

Post-hoc comparisons confirmed the findings of the previous study with respect to d_{PSE}. Namely, users ended their primary submovements significantly closer to the target (smaller d_{PSE}) when they reached directly *In* than when they reached directly *Out*, but only when reaches occurred in the hemispace contralateral to the reaching arm (i.e., reaches on the left side using the right hand, or on the right side using the left hand). There were also significant differences between reaches in other directions that involved moving inward and outward. However, these significant differences only emerged for reaches that occurred in the hemispace contralateral to the reaching arm. For reaches in the hemispace ipsilateral to the reaching arm (i.e., Left Side/Left Hand and Right Side/Right Hand), there were no significant differences in d_{PSE} across the 12 movement directions we examined (Figure 3.7).

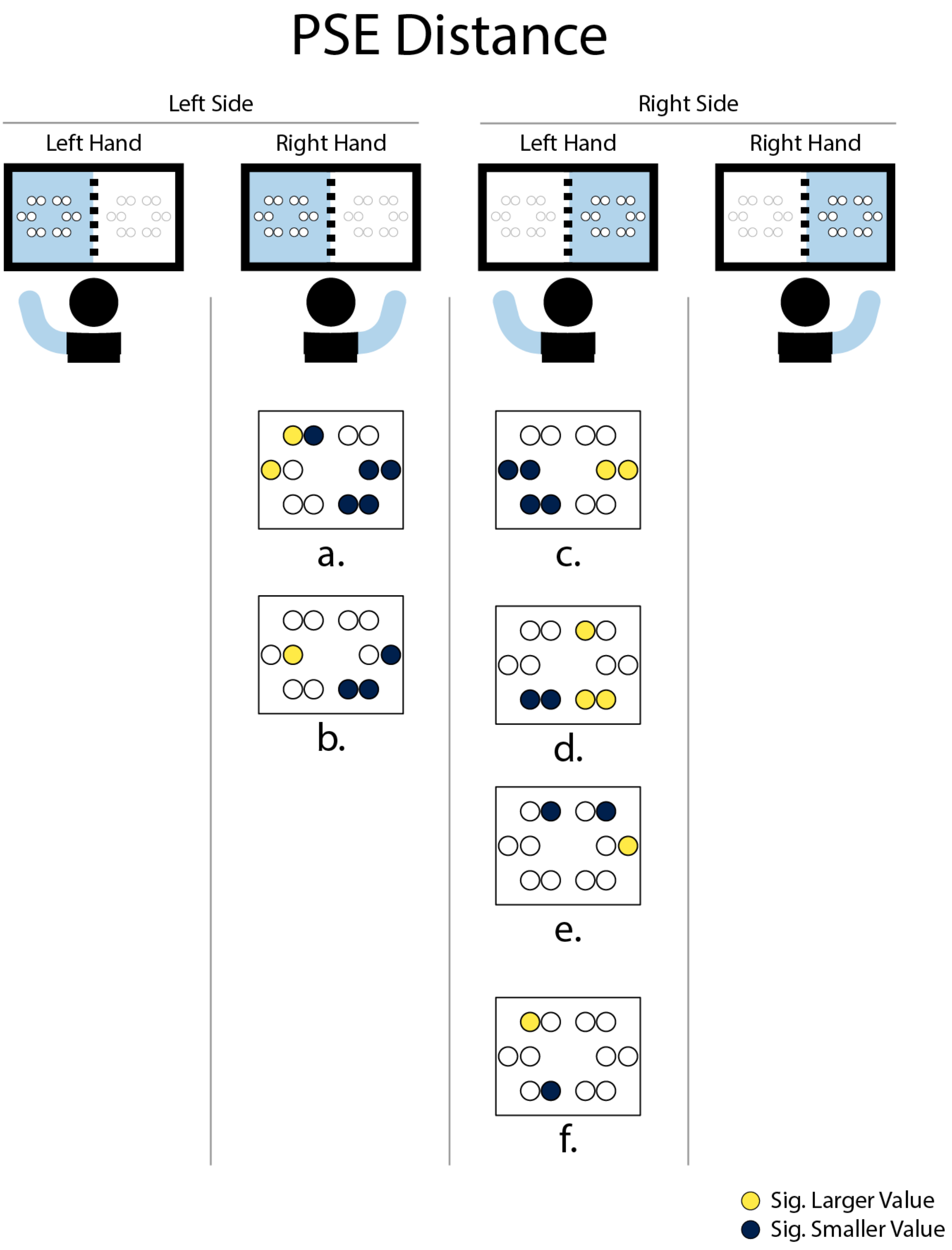
3.3.3.1 Left Side, Right Hand

When users reached on the left side of their body using their right hand, d_{PSE} was smallest (indicating primary submovements ending closer to the target) for reaches in the *In*, *InAway*, *InDown*, *InAwayDown*, and *OutAwayUp* directions, and d_{PSE} was largest for reaches in the *Out* and *OutUp* directions. Post-hoc tests indicated that d_{PSE} was significantly different between these two sets of movement directions (Figure 3.7a). d_{PSE} was also significantly larger for reaches in the *OutAway* direction than for reaches in the *In*, *InDown*, and *InAwayDown* directions, which exhibited the smallest overall d_{PSE} values (Figure 3.7b).

3.3.3.2 Right Side, Left Hand

Users exhibited a slightly different pattern of d_{PSE} values when they instead reached on the right side using their left hand. In this condition, d_{PSE} was smallest for reaches in the *In*, *InAway*, *InDown*, and *InAwayDown* directions, and largest for reaches in the *Out* and *OutAway* directions. Post-hoc comparisons revealed that d_{PSE} was significantly different between these two sets of movement directions (Figure 3.7c). Users also exhibited significantly smaller d_{PSE} for reaches in inward directions that involved moving downward (i.e., *InDown* and *InAwayDown*) than for outward reaches that involved moving downward (i.e., *OutDown* and *OutAwayDown*) and reaches in the *OutAwayUp* direction (Figure 3.7d). Some other comparisons also reached statistical significance, as summarized in Figure 3.7e and Figure 3.7f. However, the two patterns described above reflected the largest direction-dependent differences in d_{PSE} that we observed for reaches performed on the right side using the left hand.

Figure 3.7: A spatial view of how d_PSE changed as a function of movement direction for each combination of hand and side. The movement directions of opposite colors (yellow vs. black) are significantly different from each other (Tukey-corrected p < .05).



3.3.4 Spectral Arc Length ($SPARC$)

There was a significant main effect of *direction* on $SPARC$ ($\chi^2(11) = 165.97$, $p < .001$), and this effect was subsumed by a significant *hand* × *side* × *direction* interaction ($\chi^2(11) = 57.61$, $p < .001$). This indicated that $SPARC$ varied significantly as a function of movement direction, and these *direction*-dependent differences in $SPARC$ emerged differently as a function of both *hand* and *side*. Post-hoc comparisons confirmed our findings from Study 1 with respect to $SPARC$. Namely, users exhibited significantly smaller $SPARC$ values (indicating smoother movements) when reaching directly *In* than when reaching directly *Out*, and this difference reached significance for all combinations of *hand* and *side*. There were also significant differences in $SPARC$ values between reaches in the other directions, and these effects emerged differently for the different combinations of *hand* and *side* (Figure 3.4). We discuss each of these conditions in turn below.

3.3.4.1 Left Side, Left Hand

When users reached on the left side using their left hand, $SPARC$ was smallest (indicating smoother movements) for reaches in the *In* direction, and largest for reaches in the *Out*, *InAway*, and *InAwayUp* directions. Post-hoc comparisons revealed that $SPARC$ was significantly different between these two sets of movement directions (Figure 3.8a). All other comparisons fell short of statistical significance.

3.3.4.2 Left Side, Right Hand

When users reached on the left side of their body using their right hand, $SPARC$ values were smallest for reaches in all six inward directions (i.e., *In*, *InAway*, *InUp*, *InAwayUp*, *InDown*, *InAwayDown*) and the *OutDown* direction, and largest for reaches in the *Out* direction. Post-hoc comparisons revealed that $SPARC$ differed significantly between these two sets of movement directions (Figure 3.8b). $SPARC$ was also significantly smaller for reaches directly *In* (which exhibited the smallest overall $SPARC$ values) and reaches in the *OutAway* direction, which exhibited slightly smaller $SPARC$ than reaches in the *Out* direction (Figure 3.8c). All other comparisons fell short of statistical significance.

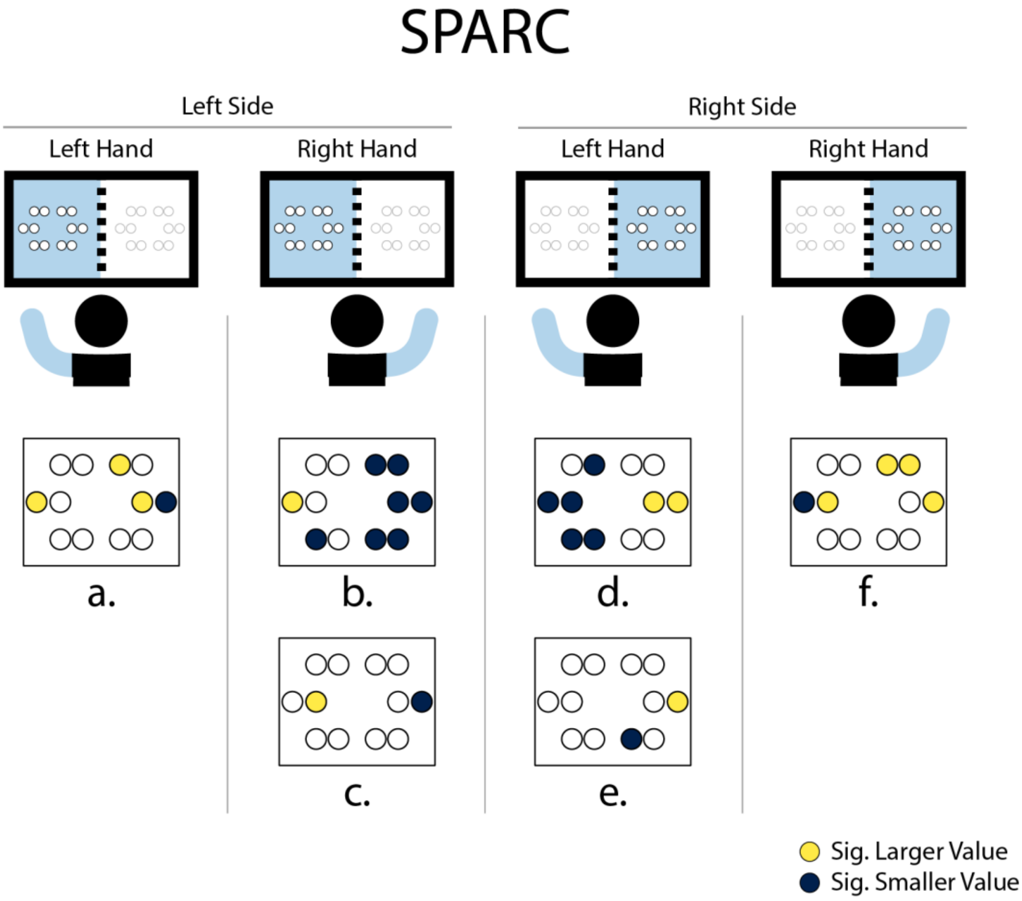
3.3.4.3 Right Side, Left Hand

A somewhat similar pattern of $SPARC$ values occurred for reaches performed on the right side using the left hand. In this condition, $SPARC$ was smallest for reaches in every inward direction except for *InUp* (i.e., *In*, *InAway*, *InAwayUp*, *InDown*, *InAwayDown*) and largest for reaches in the *Out* and *OutAway* directions. Post-hoc comparisons revealed that $SPARC$ differed significantly between these two sets of movement directions (Figure 3.8d). One other comparison reached statistical significance, as summarized in Figure 3.8e, but the pattern described above reflected the largest direction-dependent differences in $SPARC$ that emerged for reaches performed on the right side using the left hand.

3.3.4.4 Right Side, Right Hand

Finally, when users reached on the right side of their body using their right hand, $SPARC$ values were smallest for reaches directly *In*, and largest for reaches in the *InAway* direction, the *Out* direction, and both outward directions that also involved moving upward (i.e., *OutUp* and *OutAwayUp*). Post-hoc comparisons revealed that $SPARC$ differed significantly between these two sets of movement directions (Figure 3.8f). All other comparisons fell short of statistical significance.

Figure 3.8: A spatial view of how SPARC changed as a function of movement direction for each combination of hand and side. The movement directions of opposite colors (yellow vs. black) are significantly different from each other (Tukey-corrected p < .05).



3.4 Intermediate Discussion

3.4.1 Summary of Findings

Our findings in Chapter 2 revealed that (1) the kinematic properties of virtual hand reaching movements can vary when users reach in five different directions (i.e., up, down, left, right, or away), and (2) the influence of movement direction on reaching kinematics can be different depending on both the hand used to perform movements and the side of the body on which movements occur. This work also revealed some patterns concerning *how* specific kinematic metrics, including MT, v_{peak}, d_{PSE} and $SPARC$, differed across reaches in these five movement directions, for each combination of hand and side. However, it is not yet clear how the kinematic properties of virtual hand reaches change as a function of movement direction when users reach in directions that fall between the five cardinal directions that we examined in previous work. In the present study, we began to address this gap by performing a follow up study that examined a denser array of movement directions. As in Chapter 2, users reached in each direction on both the left and right sides of their body, using both their left and right arms. We addressed the same research questions as in the previous work, but for this new set of movement directions:

1. Do the kinematic properties of users' virtual hand reaching movements change when they reach in different movement directions?
2. Do some direction-dependent adaptations in users' reaching kinematics emerge differently depending on which hand is used to perform movements and/or the hemispace in which movements occur?
3. How do the kinematic properties of virtual hand reaching movements change when users encounter different values of these three task properties?

The results revealed that MT, v_{peak}, d_{PSE} and $SPARC$ all varied significantly across the 12 movement directions we examined here. (RQ 1). For all four metrics, the influence of movement direction was significantly different depending on both the *hand* used to perform movements and the *side* of the body on which movements occurred (RQ 2). Concerning *how* each kinematic metric changed as a function of movement direction, our results here yielded two principal findings.

First, as in the previous study, users exhibited faster (larger v_{peak}) and smoother (smaller $SPARC$) movements that ultimately took less time to reach the target (smaller MT) when they reached in the *In* direction (i.e., directly toward their body midline) than when they reached in the *Out* direction (i.e., directly away from their body midline). Users also ended their primary submovements significantly closer to the target (smaller d_{PSE}) when they reached in the *In* direction than when they reached in the *Out* direction, but only for reaches that occurred in the hemispace contralateral to their reaching arm (i.e., reaches on their left side using their right hand, or on their right side using their left hand). This indicated that the principal findings of the previous study generally replicated with this new set of participants.

Second, and most critically, the results also revealed how each of these four kinematic metrics changed across a set of 10 additional movement directions that either involved reaching inward (toward the body midline) or outward (away from the body midline). Across this set of directions, the influence of movement direction on reaching kinematics was (1) vastly different for each of the four kinematic metrics and (2) depended heavily on both the hand used to perform movements and the side of the body on which movements occurred. Detailed results for each kinematic metric are reported above. In the sections below, we highlight some of the most surprising findings concerning how each of these metrics varied across the 12 movement directions we examined here.

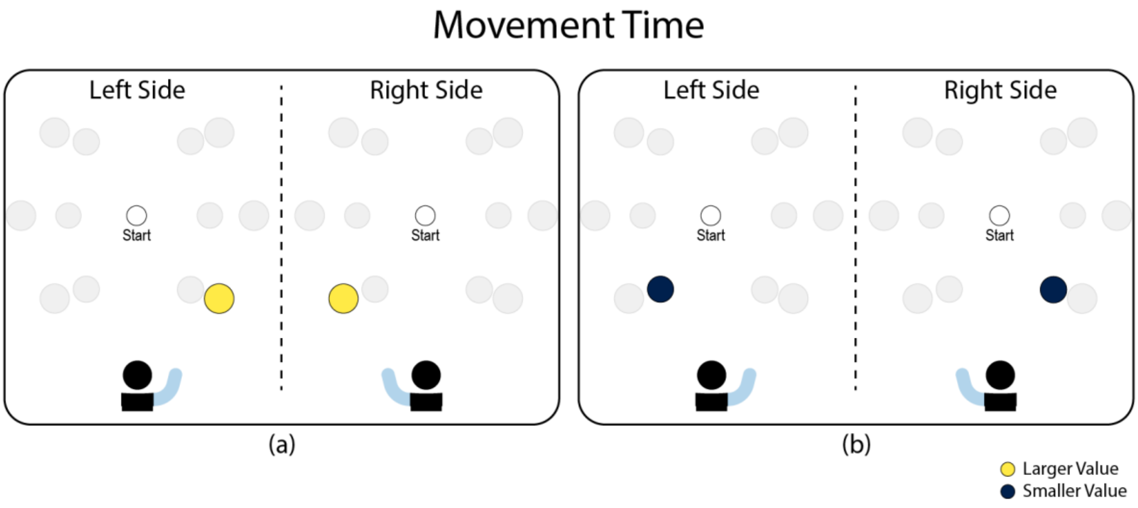
3.4.2 Surprising Direction-Dependent Patterns

3.4.2.1 Movement Time (MT)

From among our findings concerning MT, two patterns were particularly surprising. First, recall that when users reached in the hemispace contralateral to their reaching arm (i.e., Left Side/Right Hand or Right Side/Left Hand), they exhibited particularly large MT for reaches in the *InDown* direction and exhibited relatively small MT for reaches directly *In* (Figure 3.9a). Given that the targets for reaches in these two movement directions were relatively close to each other, it is surprising that users took substantially longer to reach to one than to reach to the other. From kinematic results alone, it is not yet clear precisely why users took particularly long to select targets in the *InDown* direction, but not for reaches directly *In*. However, it is possible that reaches in the *InDown* direction may have required users to engage their shoulder to move their entire lower arm down and inward at an angle, while users may have completed reaches directly *In* by bending their elbow to rotate their hand inward toward the target. Future analyses co-registering hand kinematics and motion tracking of the users' limb segments during virtual hand reaches could reveal if this was in fact the case.

Second, recall that when users reached in the hemispace contralateral to their reaching arm, they also exhibited particularly small MT when they reached in the *OutAwayDown* direction. Comparatively, when users reached in the other five directions that involved moving outward, they tended to exhibit much larger MT (Figure 3.9b). Again, from hand kinematics alone, it is not yet clear precisely why this was the case. However, one possibility is that reaches in most outward directions may have required users to engage their shoulder to a greater extent to reach farther across their body. Comparatively, given users' initial arm posture when performing reaches on the side of their body contralateral to the reaching arm, users may have been able to complete reaches in the *OutAwayDown* direction by simply extending their elbow, without needing to rely as heavily on engaging their shoulder. Again, co-registering hand kinematics with motion tracking of the users' limb segments during virtual hand reaches could reveal if this type of strategy was responsible for the kinematic pattern we observed here.

Figure 3.9: Visual summary of surprising results concerning how MT changed as a function of movement direction, for particular combinations of side and hand.



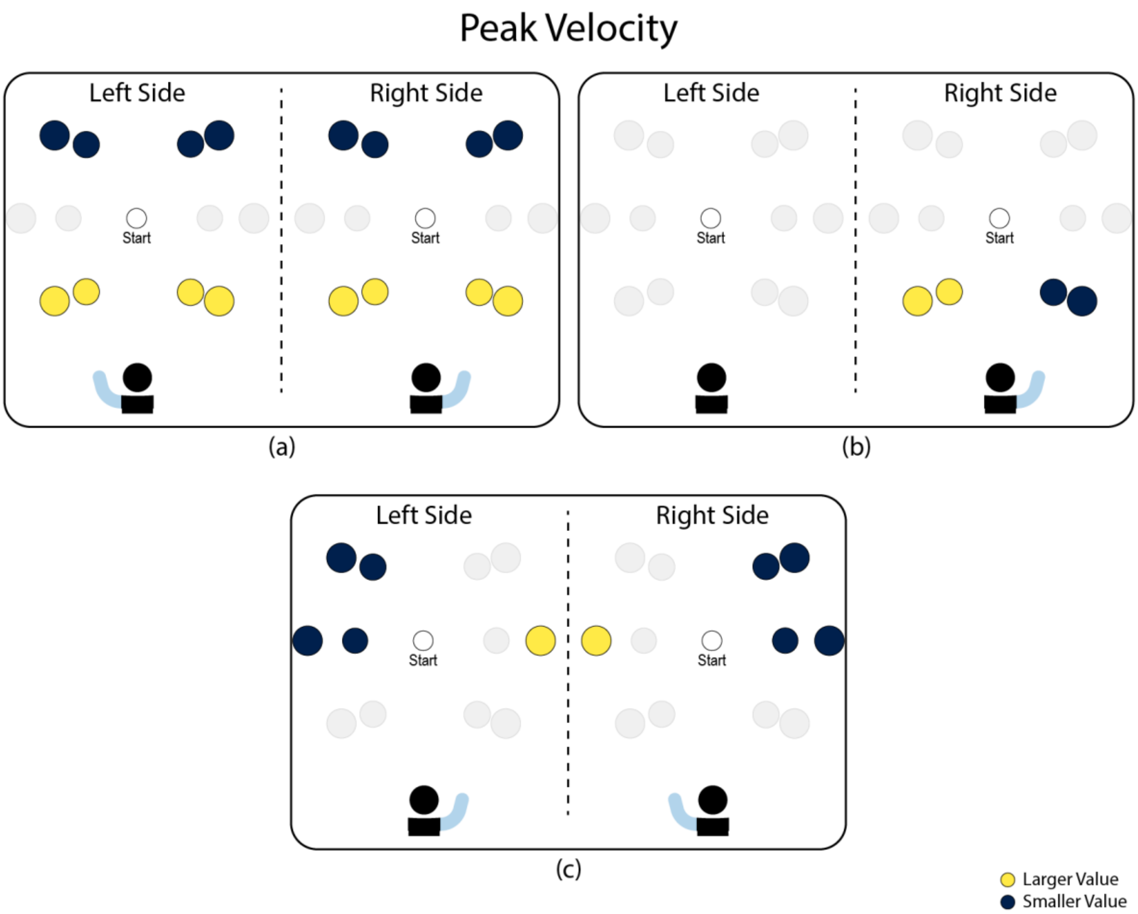
3.4.2.2 Peak Velocity (v_{peak})

Our results revealed that v_{peak} changed differently as a function of movement direction for each combination of *hand* and *side*, and each of these conditions exhibited direction-dependent differences in v_{peak} that were particularly notable. First, recall that when users reached on the left side of their body using their left hand, they exhibited smaller v_{peak} when reaching in any of the four directions that involved moving upward (i.e., *InUp*, *InAwayUp*, *OutUp*, *OutAwayUp*) than when reaching in any of the four directions that involved moving downward (i.e., *InDown*, *InAwayDown*, *OutDown*, *OutAwayDown*; Figure 3.10a). From hand kinematics alone, it is not yet clear precisely why users tended to achieve slower peak speeds when they reached upward on the left side using their left hand, compared to when they reached downward in this condition. However, the findings here suggest that, at least for reaches performed on the left side using the left hand, users may generally tend to move slower (smaller v_{peak}) when they reach in a direction that requires them to move upward than when they reach in a direction that requires them to move downward. This may be because reaches downward were performed with the aid of gravity, while reaches upward required users to reach against gravity. This finding is consistent with past results from our laboratory, which have shown that reaches that involve moving directly upward can exhibit smaller v_{peak} than reaches that involve moving directly downward. This pattern has been observed for center-out virtual hand reaches [39] and for virtual hand reaches performed on the left side of the body using the left hand (Chapter 2). When users reached on the right side of their body using their right hand, v_{peak} was again smallest for all four of the directions that involved moving upward (i.e., *InUp, InAwayUp, OutUp, OutAwayUp;* Figure 3.10a). This suggests that, just like for reaches on the left side using the left hand, users tended to move slowest (i.e., smaller v_{peak}) when they reached in directions that involved moving upward. This suggests that when users reached in the hemispace ipsilateral to their reaching arm (i.e., Left Side/Left Hand or Right Side/Right Hand), they generally tended to achieve slower speeds (smaller v_{peak}) when they reached in directions that involved moving upward than when they reached in directions that involved moving downward.

One surprising pattern only emerged for reaches performed on the right side using the right hand. Namely, in this condition, users exhibited particularly large v_{peak} when they reached in directions that involved moving both downward and inward (i.e., *InDown* and *InAwayDown*), such that v_{peak} was significantly larger for reaches in these two directions than for reaches in the other two downward directions (i.e., *OutDown* and *OutAwayDown*; Figure 3.10b). From hand kinematics alone, it is not clear precisely why users were able to achieve higher peak speeds (i.e., higher v_{peak}) when reaching in these two directions on the right side using the right hand, but not on the left side using the left hand. However, these differences might be related to differences between the dominant and non-dominant limbs in terms of the motor control strategies for which they are specialized. Specifically, since the dominant limb is specialized for predictive control, it may have been able to incorporate gravitational torques into movements more effectively than the non-dominant arm (e.g., [162,163]). Future work co-registering hand kinematics with limb segment tracking and EMG recording from the shoulders and arms could help to determine if this is in fact the case.

Finally, when users reached in the hemispace contralateral to their reaching arm (i.e., Right Side/Left Hand or Left Side/Right Hand), they exhibited uniquely large v_{peak} when they reached directly *In* and the smallest v_{peak} when they: (a) reached in the *Out* and *OutAway* directions and (b) reached in directions that involved moving both outward and upward (i.e., *OutUp* and *OutAwayUp*; Figure 3.10c). Again, from hand kinematics alone, it is not clear precisely why this pattern emerged. However, it is possible that the particularly small v_{peak} for reaches in these conditions may be related to the amount of shoulder engagement required to complete them. Specifically, given users' likely initial arm posture when selecting targets in the hemispace contralateral to their reaching arm, users may have performed reaches directly *In* with minimal shoulder engagement by slightly lowering their elbow and bending their lower arm about their elbow to reach their hand inward. Comparatively, to reach in the directions for which we observed the smallest v_{peak}, users may have instead needed to rely more heavily on engaging their shoulder to reach their arm even farther across their body. Future work co-registering hand kinematics with limb segment tracking could confirm if these types of differences in limb segment involvement are responsible for these direction-specific patterns in v_{peak} that we observed here.

Figure 3.10: Visual summary of surprising results concerning how v_{peak} changed as a function of movement direction, for particular combinations of side and hand.



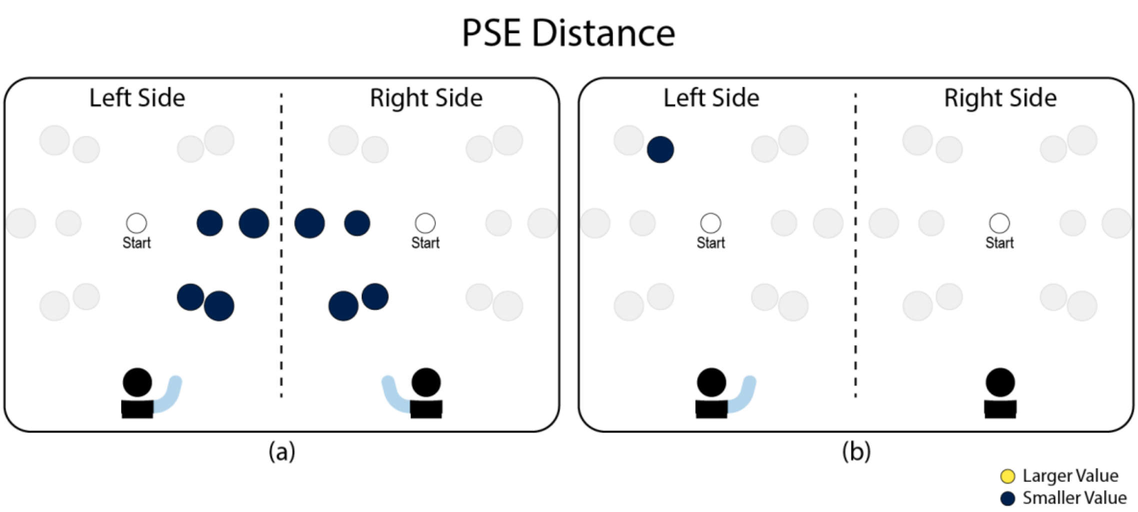
3.4.2.3 Primary Submovement Distance (d_{PSE})

The results revealed several interesting patterns concerning how d_{PSE} changed across the 12 movement directions we examined here. First, recall that d_{PSE} only changed significantly as a function of movement direction when users performed virtual hand reaches in the hemispace contralateral to their reaching arm (i.e., reaches on the left side using the right hand, or on the right side using the left hand). Interestingly, this suggests that for virtual hand reaches performed in the hemispace ipsilateral to the reaching arm (i.e., Left Side/Left Hand or Right Side/Right Hand), d_{PSE} did not vary significantly across reaches in the 12 movement directions we examined here. This does not mean that d_{PSE} was statistically equal for reaches in all 12 movement directions, but only that any differences that were present weren't large enough to achieve statistical significance. However, these results do suggest that d_{PSE} may not change drastically as a function of movement direction when users perform virtual hand reaches on the same side of their body as their reaching arm.

Second, for reaches in both conditions that involved reaching in the hemispace contralateral to the reaching arm (i.e., Left Side/Right Hand and Right Side/Left Hand), we found that d_{PSE} was particularly small for (1) reaches in the *In* and *InAway* directions and (2) reaches in inward directions that also involved moving downward (i.e., *InDown* and *InAwayDown*; Figure 3.11a). This indicates that when users reached in the hemispace contralateral to their reaching arm, they tended to end their primary submovements particularly close to the target (small d_{PSE}) when they reached in these four directions. It is not yet clear why this pattern emerged. However, the fact that it was observed when users reach in the contralateral hemispace using either their dominant or non-dominant limbs suggests that any direction-dependent differences in movement strategies or limb segment dynamics that may be responsible for this effect likely affect both the dominant and non-dominant limbs similarly. Future work co-registering hand kinematics with limb segment tracking and EMG of the chest, shoulder, and arm muscles could help to shed some light on the causes of this kinematic pattern.

Finally, when users reached in the hemispace contralateral to their reaching arm, there was one notable direction-dependent pattern in d_{PSE} values that only emerged for reaches performed using the dominant right hand, but not for reaches using the non-dominant left hand. Specifically, when users reached on the left side using their right hand, they exhibited particularly small d_{PSE} when reaching in the *OutAwayUp* direction (Figure 3.11b). However, a similar pattern did not emerge for reaches performed on the right side using the left hand. This suggests that when users reached in the hemispace contralateral to their reaching arm, they ended their primary submovements particularly close to the target (small d_{PSE}) when reaching in the *OutAwayUp* direction, but only for reaches performed using the dominant right hand. It is not yet clear precisely why reaches using the right hand on the left side exhibited this d_{PSE} benefit for reaches in this direction, while analogous reaches performed using the left hand on the right side did not. However, this may reflect differences in the control policies for which the dominant and non-dominant limbs are optimized (e.g., [162,163]), which could allow reaches using the dominant arm to gain an advantage that is not achievable for reaches using the non-dominant arm.

Figure 3.11: Visual summary of surprising results concerning how d_{PSE}changed as a function of movement direction, for particular combinations of side and hand.

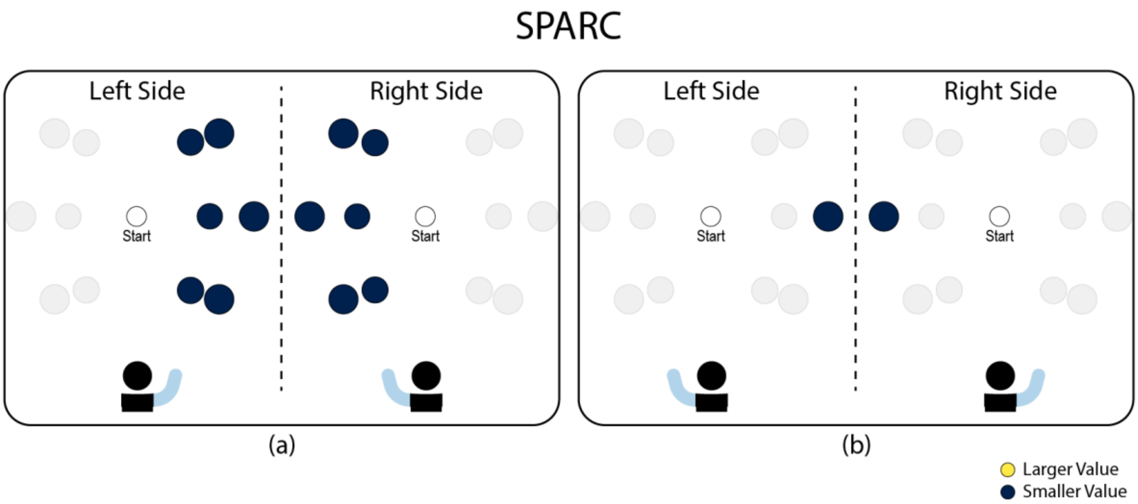


3.4.2.4 Spectral Arc Length ($SPARC$)

Recall that *spectral arc length* ($SPARC$) indexes how smooth a movement is by transforming the velocity profile for the movement into the frequency domain and then measuring the arc length of the frequency-by-power plot. In this context, a larger $SPARC$ value indicated that a movement was less smooth (i.e., involved more intermittent starting and stopping). It was particularly surprising that when users reached in the hemispace contralateral to their reaching arm (i.e., Left Side/Right Hand or Right Side/Left Hand), $SPARC$ was similarly small (indicating smoother movements) for reaches in all six of the directions that involved moving inward (i.e., *In*, *InAway*, *InUp*, *InAwayUp*, *InDown*, *InAwayDown*; Figure 3.12a). Conversely, when users reached in the hemispace ipsilateral to their reaching arm (i.e., Left Side/Left Hand or Right Side/Right Hand), $SPARC$ was smallest for reaches directly *In* but not for reaches in the other inward directions (Figure 3.12b).

This suggests that when users reached on the opposite side of their body from their reaching arm, they tended to achieve similarly smooth movements (smaller $SPARC$) when they reached in any direction that involved moving inward (Figure 3.12a). Conversely, when users reached on the same side of their body as their reaching arm, they only achieved their smoothest movements when they reached directly *In* (Figure 3.12). It is not clear precisely why this was the case, but it may have something to do with how users adapted their movement strategies to the different initial arm postures that they likely needed to assume when performing reaches in the contralateral and ipsilateral hemispaces. Considering the emerging body of evidence suggesting that $SPARC$ can provide an informative and robust measure of overall movement quality, particularly for monitoring arm function recovery during motor rehabilitation (e.g., [94,169]), it would be valuable to understand precisely why these direction- and hemispace-dependent differences in $SPARC$ emerge.

Figure 3.12:Visual summary of surprising results concerning how SPARC changed as a function of movement direction, for particular combinations of side and hand.



3.4.3 Comparisons to Previous Work

As mentioned in our summary of key related work (Section 3.1), to our knowledge no studies to-date have yet examined how the kinematic properties of virtual hand reaches change as a function of movement direction in the conditions that we examined here. However, some past work examining center-out reaches has reported some direction-dependent differences in the kinematic properties of reaches in movement directions that were similar to those we examined here. Most of this work examined center-out reaches performed to physical targets, although a few studies examined center-out virtual hand reaches performed in VR. Comparing our results in the present work with these past findings revealed if and how some of the direction-dependent differences in reaching kinematics that were observed for center-out reaches may generalize to virtual hand reaches performed on the left and right side of the body, using the left and right arms.

3.4.3.1 Away and Downward vs. Away and Upward

First, recall that work examining center-out reaches has found that there can be significant kinematic differences between reaches in directions that involve moving *away from the body and downward*, compared to reaches that involve moving *away from the body and upward*. Specifically, for center-out reaches performed in VR, there is evidence that users may exhibit larger MT [112] and smaller v_{peak} [102] when they reach in directions that involve moving *away and downward* than when they reach in directions that involve moving *away and upward*. Conversely, for 3D reaches performed to physical targets, there is some evidence that users can exhibit shorter MT when they reach *away and downward* than when they reach *away and upward* [34,128].

In the present study, we also examined reaches that involved moving away from the body and upward (i.e., *InAwayUp* and *OutAwayUp*), and reaches that involved moving away from the body and downward (i.e., *InAwayDown*, *OutAwayDown*). However, across all four combinations of *hand* and *side*, we did not observe any significant differences in MT between these two sets of reaching conditions. We did observe significant differences in v_{peak}, but these differences were in the opposite direction of the trend observed by [102]. Specifically, when we observed differences in v_{peak} between these two sets of movement directions, v_{peak} generally tended to be larger for reaches *away and downward* than for reaches *away and upward*. These patterns also emerged differently for each combination of *hand* and *side*, such that v_{peak} was not always significantly larger for reaches in every *away and downward* direction compared to every *away and upward* direction. The differences between the present results and past findings could be taken to suggest that the patterns of direction-dependent differences in MT and v_{peak} that have been observed for center-out reaches might not generalize to reaches performed on the left and right sides of the user’s body, using the dominant and non-dominant arms. However, these discrepancies may also be related to differences between the present work and past studies concerning other task properties that may have influenced users' movements, such as the height at which targets were positioned in the vertical plane.

3.4.3.2 Away and Contralateral vs. Away and Ipsilateral

Past work has also found that when users perform center-out reaches using their right arm, they can exhibit smaller MT [6,22,32,75,100,173] and larger v_{peak} [6,22,173,187,193] when they reach *away from their body and to the right*, compared to when they reach *away from their body and to the left*. Further evidence suggests that these patterns may reverse when users instead reach using the left arm, such that users can exhibit larger v_{peak} [187,193] when they reach away and to the left than when they reach away and to the right. Together, this suggests that these patterns may actually reflect kinematic differences between reaches that involve moving *away and ipsilateral* to the side of the reaching arm (e.g., away and to the right using the right hand, or away and left using the left hand), compared to reaches that involve moving *away and contralateral* to the side of the reaching arm (i.e., away and to the left using the right hand, or away and right using the left hand). However, these findings all came from reaching tasks with constraints different from those involved in virtual hand reaching. This includes 3D reaches performed to physical targets [6,32,75,100,193], 2D reaches where the hand could only move in the horizontal plane [22,187], and reaches performed without visual feedback of the hand [173]. Therefore, it is not clear if similar patterns may emerge for unconstrained 3D reaching movements performed in VR.

In the present study, we also examined reaches that involved moving away from the body and ipsilateral to the reaching arm, or away from the body and contralateral to the reaching arm (i.e., *InAway* or *OutAway*, depending on the combination of *hand* and *side*). For example, when users reached on the right side of their body using their right hand, reaches in the *OutAway* direction involved moving *away and ipsilateral* to the reaching arm, while reaches in the *InAway* direction involved moving *away and contralateral* to the reaching arm. Interestingly, for all combinations of *hand* and *side*, we did not observe any significant differences in MT between reaches in these two directions. However, we did observe differences in the predicted direction for v_{peak}, but only for reaches that occurred in the hemispace contralateral to the reaching arm (i.e., reaches on the right side using the left hand, or on the left side using the right hand). This suggests that users may exhibit this pattern of v_{peak} benefits (i.e., larger v_{peak}) for both center-out reaches and reaches that occur in the hemispace contralateral to the reaching arm, but not for reaches in the ipsilateral hemispace (i.e., reaches on the right side using the right hand, or on the left side using the left hand).

The differences between our findings here and past results suggest that users may adopt different movement strategies when they perform goal-directed reaching movements in the real world and VR. These strategies may emerge in part as a response to the different arm postures involved in reaching to select targets in VR. Specifically, most of the past work showing kinematic benefits for center-out reaches that involve moving *away and ipsilateral* to the reaching arm compared to reaches *away and contralateral* to the reaching arm has studied reaches performed in the horizontal plane. For these reaches, the elbow is typically held at the same height as the wrist to allow users to move between targets position on a tabletop. Comparatively, when users reach to select targets in a VR environment, they often begin reaches with their wrist positioned higher than their elbow. It is therefore possible that when users perform reaching movements that begin with this initial posture, they may exhibit larger v_{peak} when reaching *away and ipsilateral* to the reaching arm compared to reaches *away and contralateral* to the reaching arm without also exhibiting a corresponding reduction in MT.

4 Study 3: Does Arm Length Moderate the Effects of Direction, Hand, and Hemispace?

In the previous two studies, we examined the kinematic properties of virtual hand reaches that involved moving in a range of different *movement directions*, on either the left or right *side* of the user's body (i.e., hemispace), using either the dominant or non-dominant *hand* (i.e., hand dominance). This work revealed that several kinematic properties of virtual hand reaches changed when users performed reaches in different movement directions, including *movement time* (MT), *peak velocity* (v_{peak}), *spectral arc length* ($SPARC$), and *primary submovement endpoint distance* (d_{PSE}). Furthermore, we found that the influence of movement direction on these properties was different depending on both the hand used to perform movements and the side of the body on which movements occurred. Our results also revealed several patterns concerning *how* each of these kinematic properties changed for reaches in different movement directions, for reaches performed on each side of the body using each hand (summarized in Section 4.1 below).

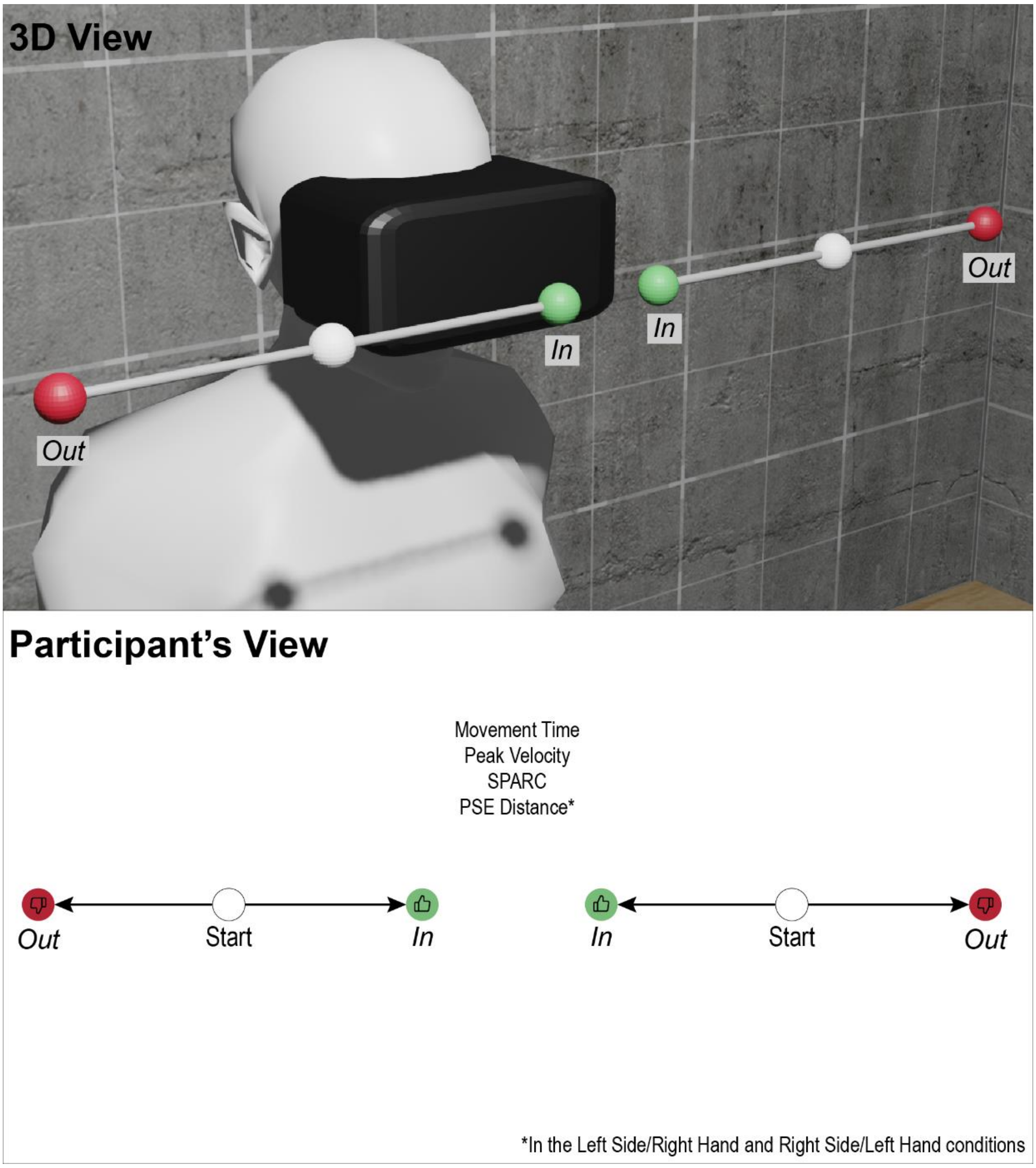
The first two studies provided a novel empirical account of how users adapt the kinematic properties of their virtual hand reaches when they reach in different *directions*, and how these effects of *direction* on reaching kinematics are different depending on both the *hand* used to perform movements and the *side* of the body on which movements occur. In this third and final study, we examined one additional factor that may also moderate the effects of movement direction on reaching kinematics: individual differences in *arm length*. Based on past work in movement science, there is reason to suspect that the effects of movement direction on reaching kinematics may be different for users with shorter arms than for users with longer arms (see Section 1.4.4 for details). If this is the case, then the largest effects we observed in the previous studies may emerge differently for users with different arm lengths. However, while some limited work on related topics suggests that individual differences in arm length may influence reaching kinematics (see Section 1.5.4 for details), to our knowledge no study to-date has yet examined if and how individual differences in arm length influence the kinematic properties of virtual hand reaches or goal-directed reaches performed in any context. As such, it is also not yet clear if and how individual differences in arm length may moderate the effects of movement direction on reaching kinematics, for reaches performed on either side of the body using either hand.

4.1 Does Arm Length Moderate Effects from Chapters 2 and 3?

To begin addressing this question, we examined if and how the largest effects of movement direction on reaching kinematics that we observed in the previous studies emerged differently for users with shorter arms than for users with longer arms. We summarize these effects below, and we then consider how they may emerge differently for users with shorter arms than for users with longer arms.

First, recall that users exhibited significantly faster (larger v_{peak}) and smoother (smaller $SPARC$) movements that took much less time to reach the target (smaller MT) when they reached directly toward their body midline (i.e., the *In* direction) than when they reached directly away from their body midline (i.e., the *Out* direction; Figure 4.1). These effects were present for reaches performed on either side of the body, using either hand. We also found that users ended their primary submovements much closer to the target (smaller d_{pse}) when they reached in the *In* direction than when they reached in the *Out* direction. However, this effect only emerged when users reached on the side of the body contralateral to their reaching arm (i.e., reaches on the left side using the right hand, or on the right side using the left hand). These effects were present in both previous studies, suggesting that these are relatively consistent effects that were not simply unique to one group of participants.

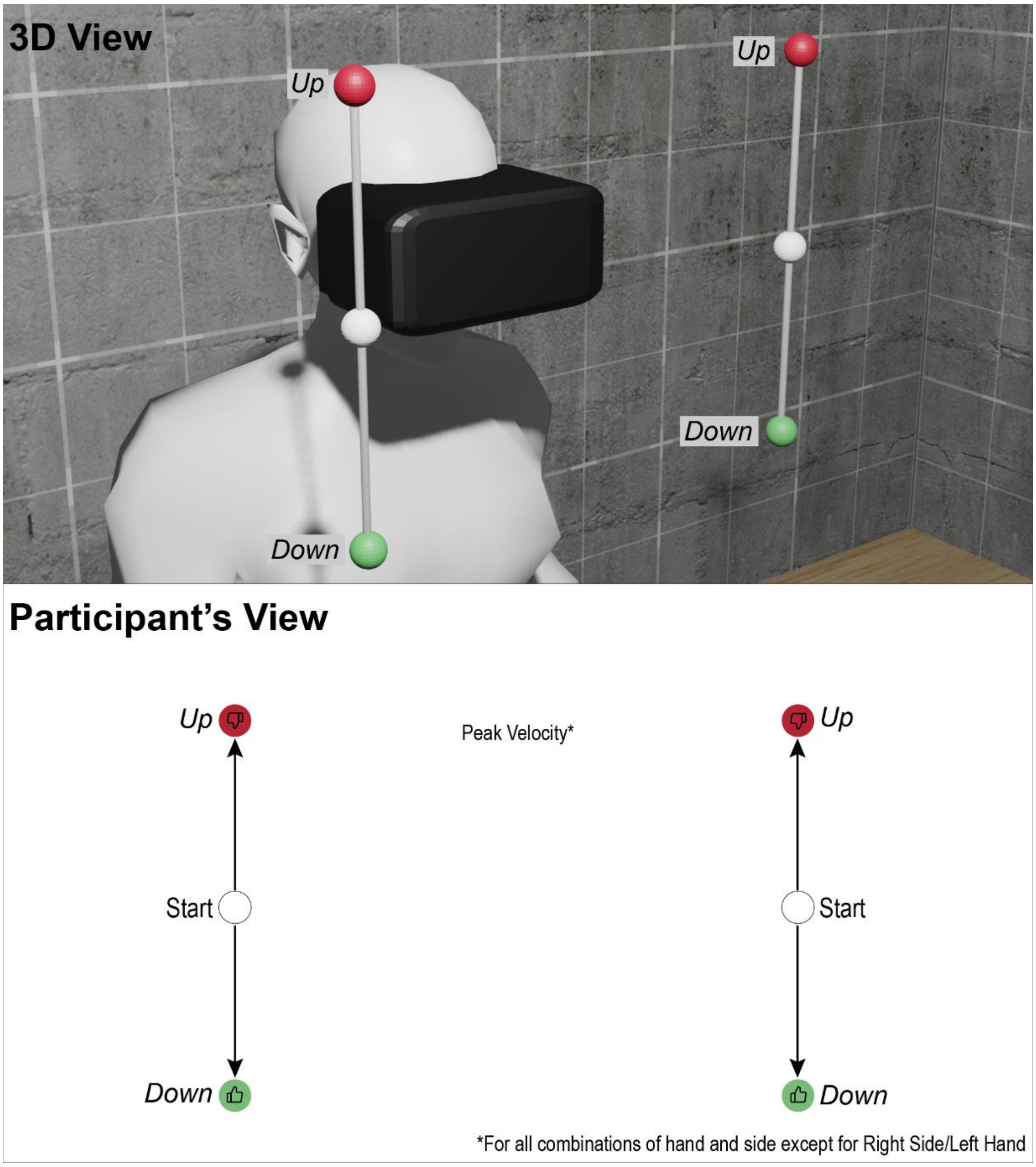
Figure 4.1: Spatial summary of the differences in reaching kinematics between reaches in the *In* and *Out* directions.



Second, recall that users exhibited significantly faster movements (larger v_{peak}) when they reached directly downward (i.e., the *Down* direction) than when they reached directly upward (i.e., the *Up* direction; Figure 4.2). This effect was large enough to reach statistical significance for reaches that involved three out of the four combinations of *hand* and *side*. Specifically, users exhibited significantly larger v_{peak} when reaching *Down* than when reaching *Up*, but only when they reached on their left side using their left hand, on their left side using their right hand, or on their right side using their right hand (Figure 4.2). When users reached on their right side using their left hand, v_{peak}

was still slightly larger for reaches *Down* than for reaches *Up*. However, this difference was not large enough to reach statistical significance. We initially observed this pattern in Chapter 2, but the results in Chapter 3 were also generally consistent with this finding. Specifically, in Chapter 3, we found that users tended to exhibit smaller v_{peak} when they reached in directions that involved moving downward than when they reached in directions that involved moving upward, and these differences were present for the combinations of *hand* and *side* for which we observed similar effects in Chapter 2. Furthermore, review of the data from additional target locations that were not examined in the Chapter 3 analysis (Appendix E) suggests that the pattern of differences in v_{peak} between reaches in the *Down* and *Up* directions replicated for the set of participants examined in Chapter 3. As in Chapter 2, v_{peak} was larger for reaches in the *Down* direction than for reaches in the *Up* direction, but this difference was relatively small for one combination of *hand* and *side* (i.e., reaches on the right side using the left hand).

Figure 4.2: Spatial summary of the differences in reaching kinematics between reaches in the Up and Down directions.



In the present study, we examined if and how each of these effects may emerge differently for users with different arm lengths. For example, from examining the differences between reaches in the *In* and *Out* directions, we know that when users reached on the left side of their body using their right hand, they took an average of approximately 100 ms less time (i.e., smaller *MT*) to reach in the *In* direction than to reach in the *Out* direction. However, this result only tells us about a trend that is observed in the aggregate, when the data are averaged across individual users. By examining results at the level of individual users, we may find that this effect emerges differently for users with shorter arms than for user with longer arms. For example, we might find that when a user with shorter arms reaches on the left side of their body using their right hand, they take 200 ms less time (smaller MT) to reach in the *In* direction than to reach *Out* direction. However, we might find that when a user with longer arms performs the same movement, they only take 50 ms less time to reach in the *In* direction than to reach in the *Out* direction. Alternatively, this effect may emerge similarly for all users, such that both users with shorter arms and users with longer arms take about 100 ms less time (smaller MT) to reach *In* than to reach *Out*.

4.2 The Present Study

In the present work, we examined if and how individual differences in *arm length* moderate the largest effects of movement direction on reaching kinematics that we observed in the previous two studies. We recruited a new sample of 40 participants with a broad range of arm lengths and had them perform the same virtual hand reaching task used in Chapter 3. We addressed the following research questions:

1. Do the effects of movement direction on MT, v_{peak}, $SPARC$, and d_{PSE} for reaches on each side of the body using each hand depend on users' arm length?
2. If so, do the differences in MT, v_{peak}, $SPARC$, and d_{PSE} between reaches in different directions tend to become larger or smaller as arm length increases?

4.3 Methods

4.3.1 Participants

This study included a unique set of 40 participants who did not participate in the two previous studies. Participants were recruited from the undergraduate, graduate student, and employee population at the University of Virginia (20 female, mean age = 21.68, range = 18-39). All participants had normal or corrected-to-normal vision and reported having no ailments that impacted their arm mobility. All participants expressed a strong right-hand preference, with scores greater than 40 (M = 80.83, SD = 14.62) on the Edinburgh Handedness Inventory [138]. Twenty-seven participants reported having had at least some previous experience with the Oculus Quest or another consumer VR headset. Of these participants, four considered themselves to be expert users of at least one VR system. The remaining participants reported having no previous experience with VR.

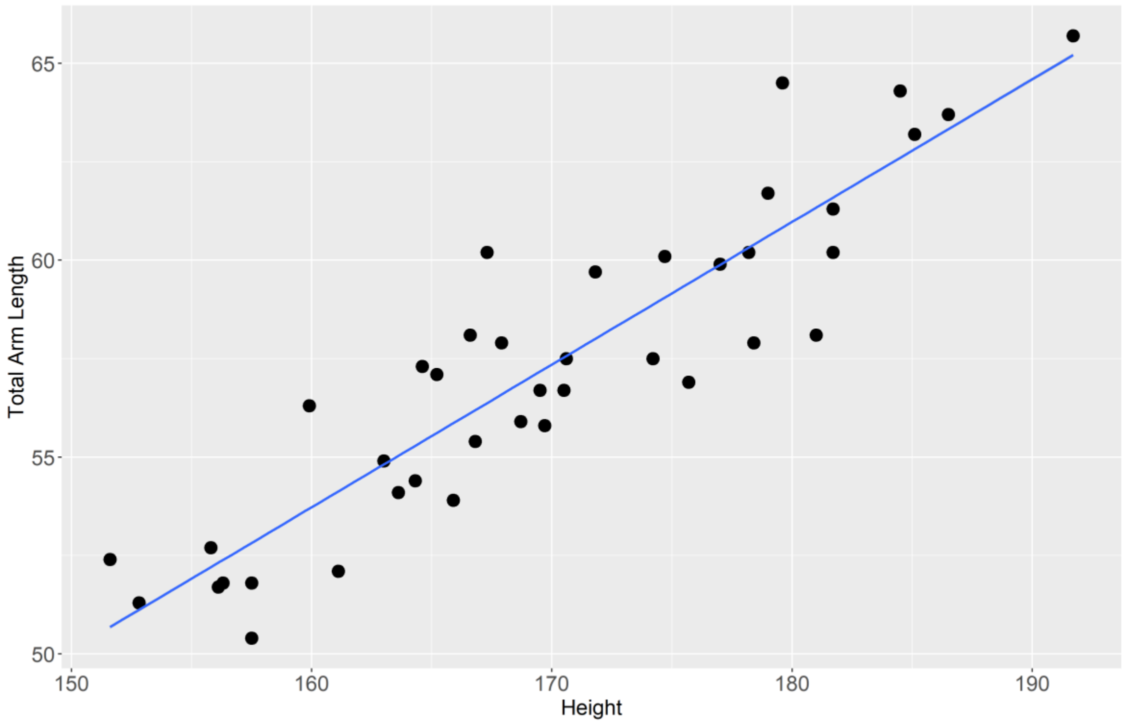
To examine how arm length influences reaching kinematics, it was important to ensure that our participants exhibited sufficient variability in arm length. Therefore, participants were recruited using a stratified sampling strategy based on their height. For each biological sex, we identified five height ranges corresponding to 20% percentile increments (i.e., 1^{st}-20^{th} percentile, 21^{st}-40^{th} percentile etc.). These increments were defined using height percentiles for the United States civilian population, as synthesized from the combined 2007-2010 NHANES anthropometric dataset [33]. We then recruited four participants with heights that fell within each of the five percentile ranges, for each biological sex. This yielded our full set of 40 participants (2 sexes × 5 percentile ranges x 4 participants per range).

We chose this approach because height correlates strongly with arm length, and participants were much more likely to know their own height than to know their arm length. This was useful for scheduling, since prospective participants could easily provide an estimate of their height that could be used to associate them with the percentile range within which they would most likely fit. When participants arrived for the study, their heights were measured using the procedures described below to ensure that they were assigned to the appropriate percentile range. The anthropometric characteristics for this sample of participants are summarized in Table 4.1 below. As expected, arm length correlated very strongly with height (r = 0.91), and participants exhibited a broad range of different arm lengths (Figure 4.3).

Table 4.1: Summary of the anthropometric measurements for the participants in the present study, in centimeters.

Measure	Mean	SD	Min	Max
Height	170.0	9.93	152.0	192.0
Upper Arm (Acromiale-Radiale)	31.6	2.3	28	37.5
Lower Arm (Radiale-Stylion)	25.7	1.85	21.5	29.6
Total Arm Length	57.3	3.95	50.4	65.7

Figure 4.3: Plot of the relationship between height and arm length among participants in the present study.



4.3.2 Procedures

The procedure and experimental task were the same as in Chapter 3, except that in the present study we also measured anthropometric characteristics for each participant. At the beginning of the experiment, we measured the participant's height to confirm the height percentile range to which they belonged. Height was measured using a 90-degree headboard and a girth tape that was fixed to a wall and checked for height and vertical positioning. We then used a segmometer (Cescorf Inc.; Figure 4.4) to measure the length of the participant's upper arm (i.e., the acromiale-radiale segment) and lower arm (i.e., the radiale-stylion segment). All anthropometric measures were performed using the procedures outlined in [137], which align with the standards forwarded by the International Society for the Advancement of Kinanthropometry (ISAK).

Figure 4.4: The segmometer that was used to measure each participant's arm length in the present study.

4.3.3 Statistical Analysis

4.3.3.1 Kinematic Differences Between Reaches in the *In* and *Out* Directions

Data collection and pre-processing were performed using the same procedures as in the previous two studies. To address our research questions for the differences in MT, v_{peak}, $SPARC$, and d_{PSE} between reaches in the *In* and *Out* directions, we extracted the set of 3200 trials that involved reaches in the *In* and *Out* directions. Of these trials, 190 (5.9%) were identified as containing errors using the same criteria employed in the previous two studies (i.e., multiple button presses, or MT greater than 3 $\times IQR$ above the third quartile). No trials were found to contain tracking loss. The remaining 3010 trials (94.1%) were submitted for further analysis.

Recall that we were first interested in understanding if the differences in MT, v_{peak}, $SPARC$, and d_{PSE} between reaches in the *In* and *Out* directions depend on users' arm length (RQ 1) and if these differences tend to become larger or smaller as arm length increases (RQ 2). To address these questions, we used multilevel linear modeling [104] to (1) examine the effect of movement direction (1 if *In*, 0 if *Out*) on each kinematic metric, for each combination of *hand* and *side*, (2) include random slopes to estimate how much the effect of *direction* varied across users, and (3) examine if individual differences in arm length accounted for a significant proportion of this variance. We fitted a separate multilevel linear model for each kinematic metric, for each combination of *hand* and *side* (i.e., Left Side/Left Hand, Left Side/Right Hand, Right Side/Left Hand, and Right Side/Right Hand). Each model was fitted using the bottom-up procedure described by [86]. For each model, we first fit a null model containing only random intercepts for participants. We then added a fixed effect for *direction* (1 if *In*, 0 if *Out*), included random slopes for movement direction, and then added a cross-level *direction* × *arm length* interaction. Likelihood ratio tests indicated if there was a significant effect of *direction* or a significant *direction* × *arm length* interaction for each metric, for each combination of *hand* and *side*. The p-values for these tests were corrected using Holm's step-down procedure [85] to control the familywise error rate at 5%. For each combination of *hand* and *side*, the likelihood ratio test for the fixed effect of *direction* indicated if each metric was significantly different between reaches in the *In* and *Out* directions. The likelihood ratio test for the *direction* × *arm length* interaction then indicated if the effect of *direction* on each metric emerged differently for different users depending on their arm length.

4.3.3.2 Kinematic Differences Between Reaches in the *Up* and *Down* Directions

We used the same analysis approach described above to examine differences in v_{peak} between reaches in the *Up* and *Down* directions. For this analysis, we extracted the set of 3200 trials that involved reaches in either the *Up* or *Down* directions. Of these trials, 203 (6.3%) were identified as containing errors using the same criteria described above. The remaining 2997 trials (93.7%) were submitted for further analysis. The statistical analyses for these effects followed the same procedure described above, except that the dummy variable encoding movement direction indicated whether reaches involved moving in the *Up* or *Down* direction (1 if *Up*, 0 if *Down*).

4.3.3.3 Model Assumptions and Diagnostics

The assumptions for all models were checked by inspecting plots of the trial- and participant-level residuals for indicators of outliers or non-normality. In all cases, residuals were approximately normally distributed, and there was no evidence of strong heteroscedasticity. To ensure that each result was not driven by a few unusual but highly influential observations, influence diagnostics (Cook's D) were calculated for observations at both the trial and participant levels. Any potential highly influential observations were further investigated by refitting the models without them. See Appendix G for a detailed account of this sensitivity analysis.

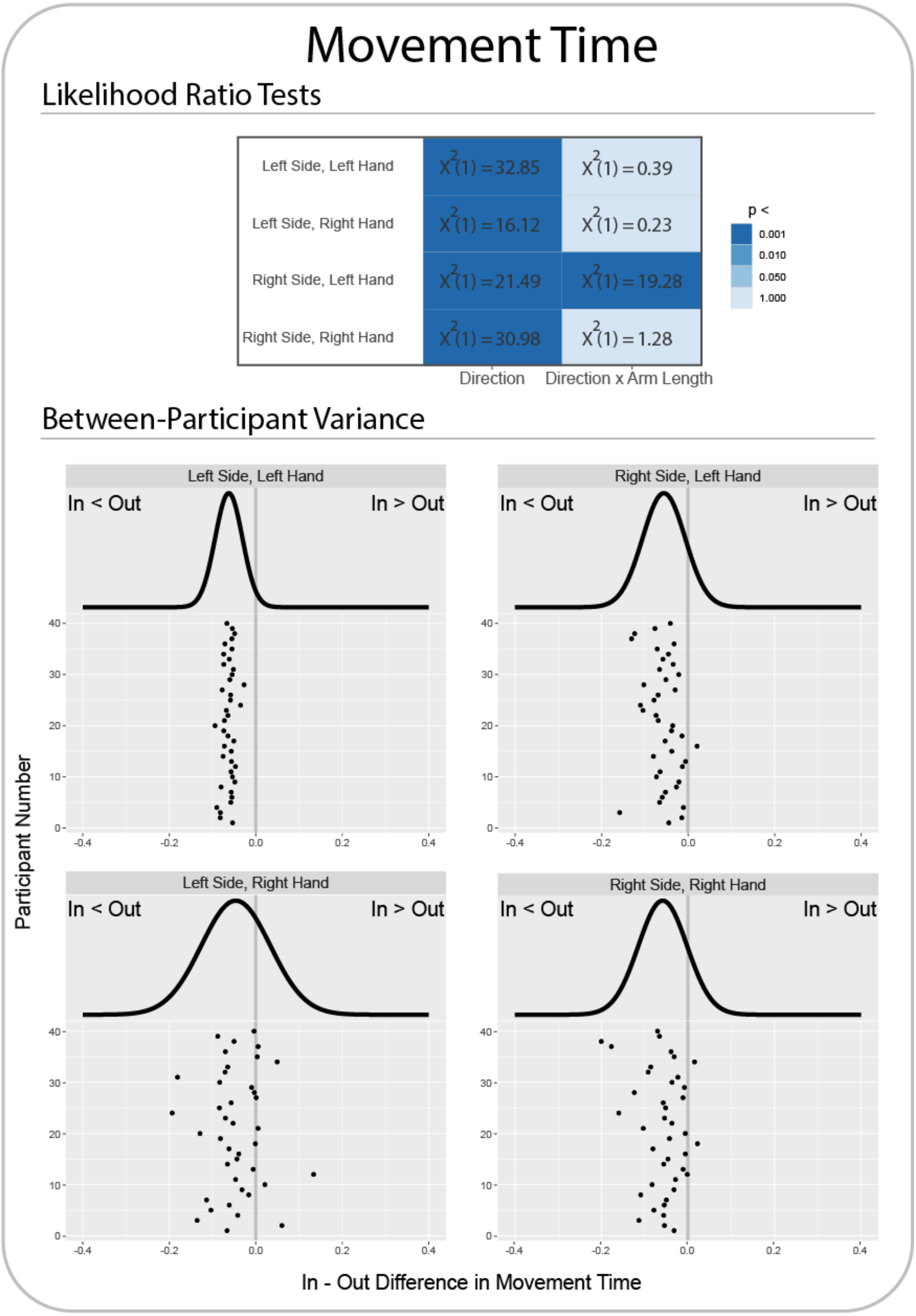
4.4 Results

4.4.1 Differences Between the *In* and *Out* Directions

4.4.1.1 Movement Time (*MT*)

For all four combinations of *hand* and *side*, *MT* was significantly different between reaches in the *In* and *Out* directions (Figure 4.5, top panel). On average, users took less time to complete movements when they reached *In* than when they reached *Out*, and this effect was present for all four combinations of *hand* and *side* (Figure 4.5, bottom panel). This was consistent with the pattern observed in previous studies. Random effects analysis indicated that for reaches performed on the left side of the body using the left hand, this effect was relatively consistent. All users took approximately 62.5 ms less time (smaller *MT*) to reach *In* than to reach *Out* (Figure 4.5, bottom panel). However, for reaches that involved the other three combinations of *hand* and *side*, this effect was less consistent across users. Some users took much less time (smaller *MT*) to reach *In* than to reach *Out*, while other users took a similar amount of time to reach in the two directions. For a few users, reaches in the *In* direction actually took slightly *longer* to perform (larger *MT*) than reaches in the *Out* direction (Figure 4.5, bottom panel).

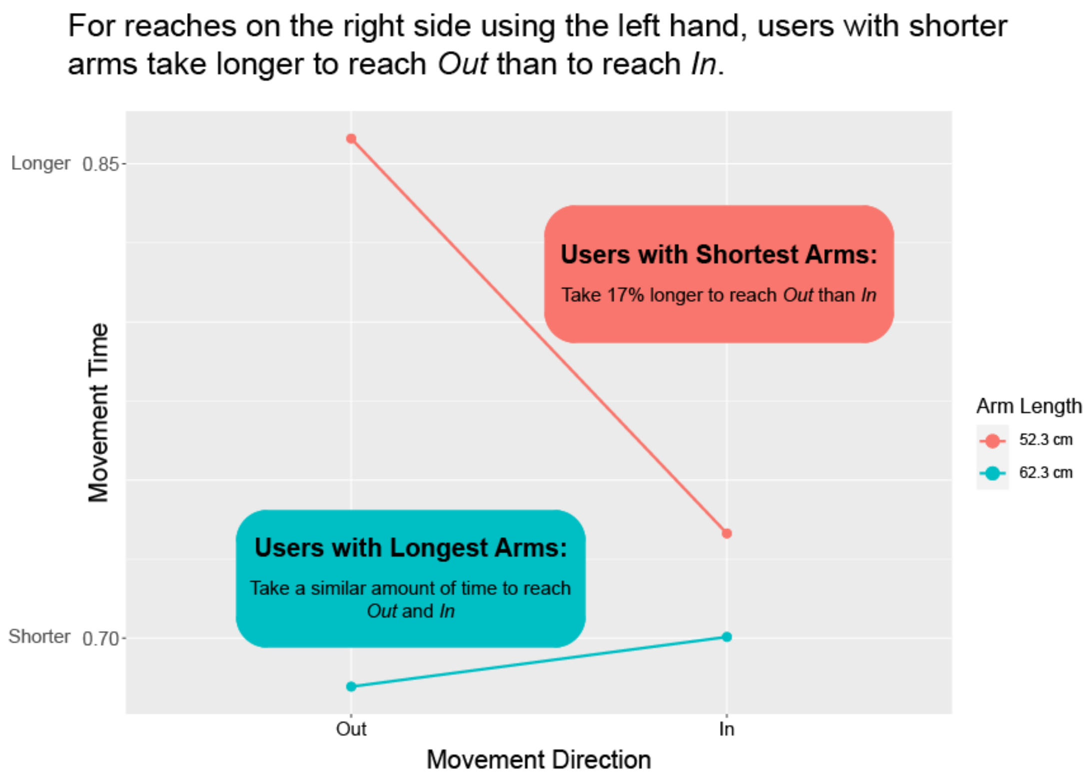
Figure 4.5: At the top, the results of the likelihood ratio tests for the effect of *direction* and the *direction* x *arm length* interaction for movement time (MT). At the bottom, two different visual summaries of how the difference in MT between reaches in the In and Out directions (in seconds) varied across participants, for each combination of *hand* and *side*.



For reaches on the right side using the left hand, there was a significant *direction* × *arm length* interaction effect. This indicated that there was a significant linear relationship between users' arm length and the difference in MT between reaches in the *In* and *Out* directions, as summarized in Figure 4.6. The parameter estimates for this effect revealed that users with shorter arms took much less time to reach targets (smaller MT) when they reached in the *In* direction than when they reached in the *Out* direction. However, as arm length increased, the MT benefit associated with reaching *In* compared to reaching *Out* became smaller. For users with the longest arms, there was no MT benefit for reaching *In* compared to reaching *Out* (Figure 4.6). The final model for this effect exhibited a singular fit, reflecting the fact that after arm length was included as a predictor the remaining random effect variance for *direction* estimated as very close to zero. To ensure that this pattern of results was not an artifact of the model fitting process, we refitted the model using Bayesian MCMC estimation and the default minimally informative priors implemented in the rstanarm package [71]. The resulting model showed the same general relationship between arm length and the difference in MT between reaches in the *In* and *Out* directions, confirming our results. We discuss this effect in more detail in Section 4.5.3 below.

For the other three combinations of *hand* and *side*, the *direction* × *arm length* interaction effects did not reach significance. This was understandable for reaches on the left side using the left hand, since in this condition there was not much between-user variability to explain in the first place. However, for the remaining two conditions with the right hand (Left Side/Right Hand and Right Side/Right Hand), the MT benefit for reaches *In* compared to reaches *Out* was larger for some users than for others. As such, these effects emerged differently for different users, but this variation was not significantly related to individual differences in arm length ($p > .05$ for the likelihood ratio tests for both effects).

Figure 4.6: Predicted values from the multilevel model for reaches on the right side using the left hand, for users with particularly short arms (52.6 cm; pink line) and particularly long arms (62.3 cm; blue line) arms. This plot summarizes how movement time (MT; y-axis) changed as a function of movement direction (*In* or *Out*, x-axis) for users with the shortest compared to the longest arms.

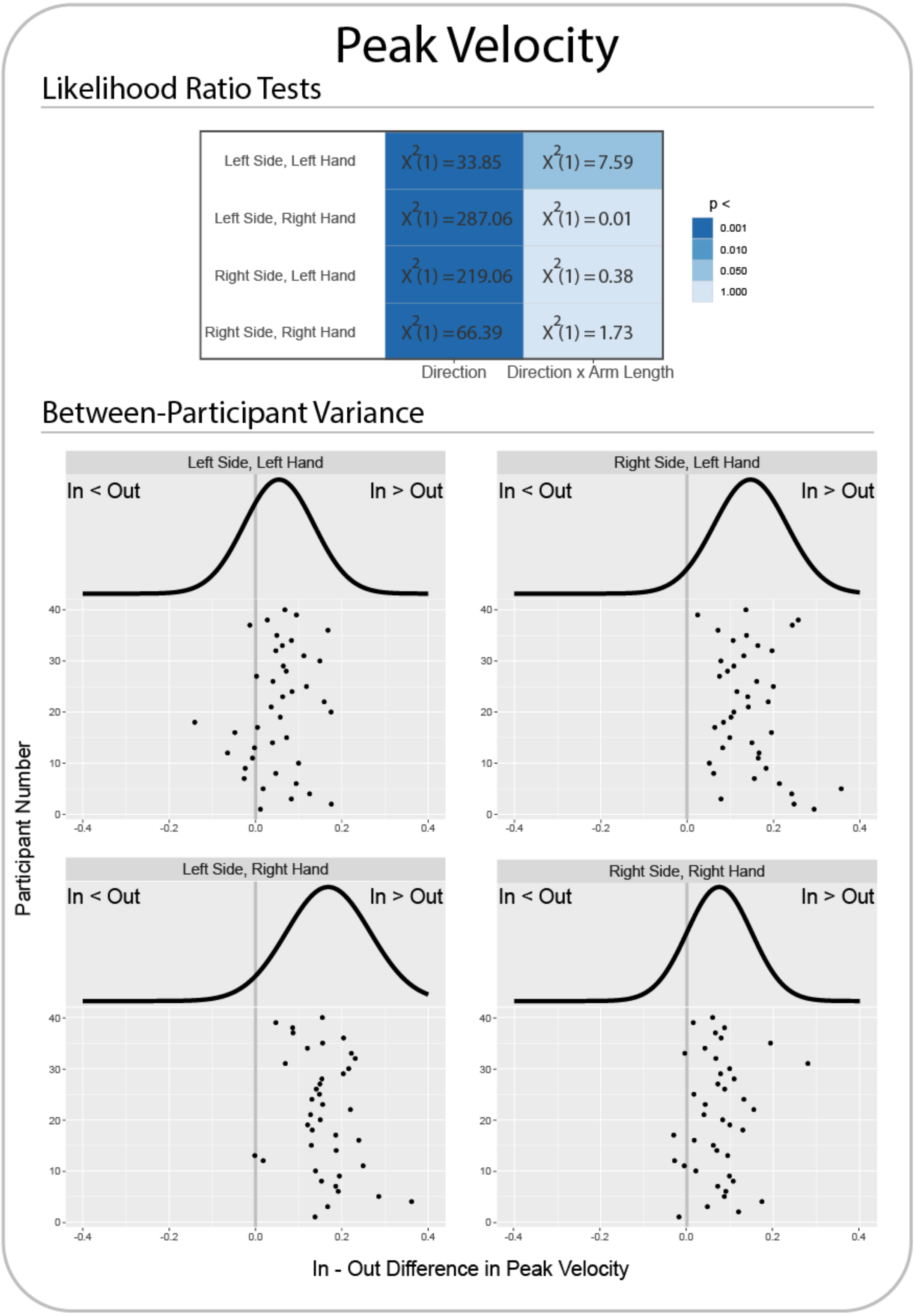


4.4.1.2 Peak Velocity (v_{peak})

For all four combinations of *hand* and *side*, v_{peak} was significantly different between reaches in the *In* direction and reaches in the *Out* direction (Figure 4.7, top panel). On average, users moved faster (larger v_{peak}) when they reached *In* than when they reached *Out*, and this effect was present for all four combinations of *hand* and *side* (Figure 4.7, bottom panel). This was consistent with a pattern observed in Chapters 1 and 2. Random effects analysis indicated that for all four combinations of *hand* and *side*, the difference in v_{peak} between reaches *In* and reaches *Out* varied considerably across users (Figure 4.7, bottom panel). Some users reached much faster (larger v_{peak}) when they reached *In* than when they reached *Out*, while others only reached slightly faster when reaching *In* than when reaching *Out*. In a few cases, users achieved similar speeds when they reached in the *In* and *Out* directions, and a few even moved slightly slower when reaching *In* than when reaching *Out*.

For reaches on the left side of the body using the left hand, likelihood ratio tests for the *direction* × *arm length* interaction suggested that there was a significant relationship between users' arm length and the difference in v_{peak} between reaches in the *In* and *Out* directions. However, further investigation revealed that this effect was driven by the data from one unusual but highly influential participant (Participant 18; Cook's D = 0.375). This participant had the longest arm length (65.7 cm) and also exhibited an unusually small difference in v_{peak} between reaches in the *In* and *Out* directions, which drove the slope for the *direction* × *arm length* interaction away from zero. When the model was refitted without the data from this participant, the *direction* × *arm length* interaction no longer reached significance ($\chi^2(1) = 4.11$, *p* = .34; see Appendix G for details). Furthermore, for the remaining three combinations of *hand* and *side*, the *direction* × *arm length* interaction effects also did not reach significance (Figure 4.7, top panel). Together, these findings indicated that the v_{peak} benefit for reaches *In* compared to reaches *Out* was larger for some users than for others, but this variation was not related to individual differences in arm length.

Figure 4.7: At the top, the results of the likelihood ratio tests for the effect of direction and the direction x arm length interaction for peak velocity (v_{peak}). At the bottom, two different visual summaries of how the difference in v_{peak} between reaches in the *In* and *Out* directions (in Unity units/s) varied across participants, for each combination of *hand* and *side*.



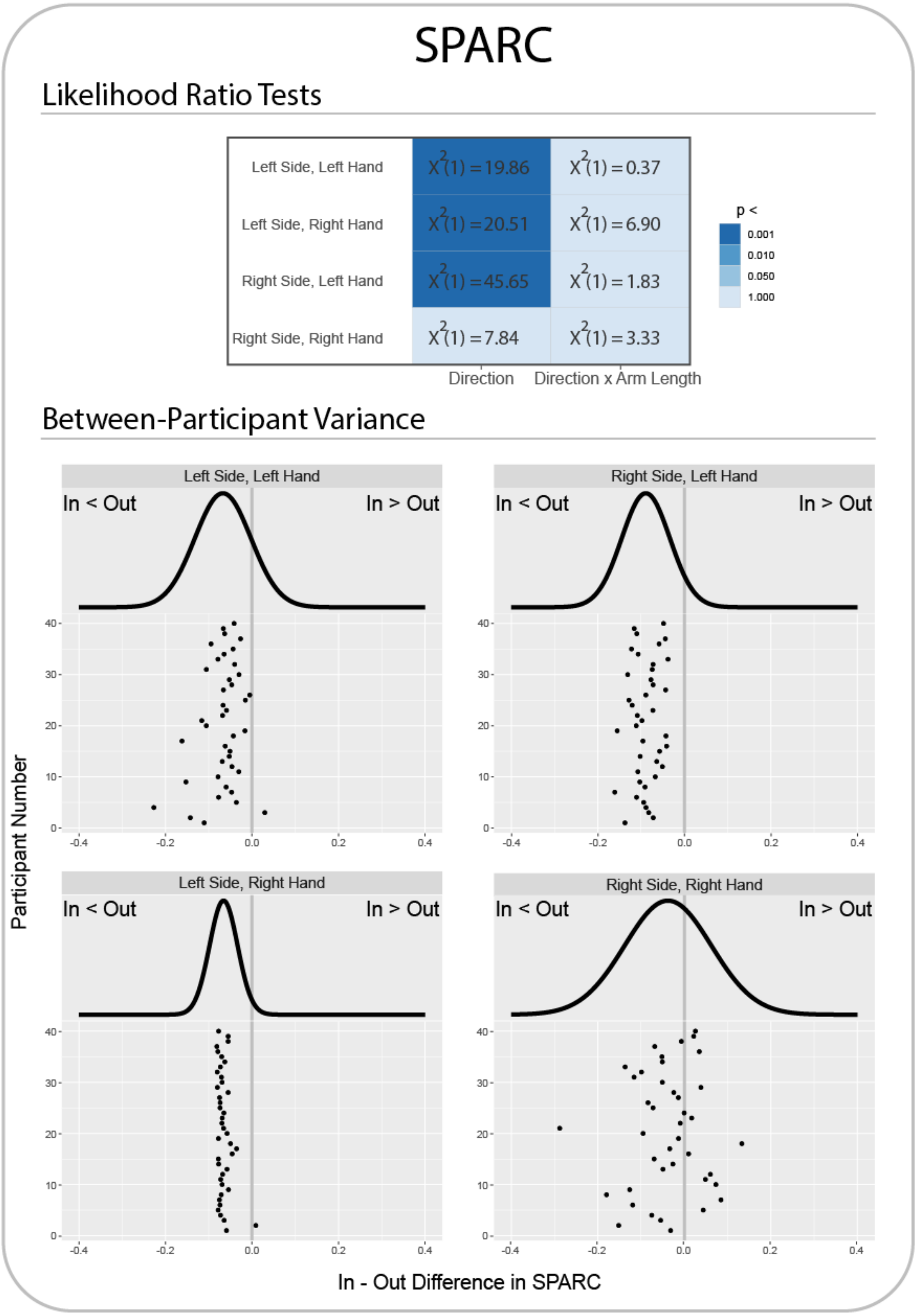
4.4.1.3 Spectral Arc Length ($SPARC$)

As in the previous studies, users tended to exhibit smoother movements (smaller $SPARC$) when they reached *In* than when they reached *Out*. This trend was present for all four combinations of *hand* and side, but it fell just short of statistical significance for reaches that occurred on the right side using the right hand (p = .056; Figure 4.8, top panel). These findings were generally consistent with the results of past work, which indicated that when users reach on either side of their body using either hand they tend to move more smoothly when they reach *In* than when they reach *Out*.

Random effects analysis revealed that when users reached on the left side of their body using their right hand, this effect was relatively consistent across users. For all but one user, the $\boldsymbol{SPARC}$ measure was approximately 0.66 smaller (i.e., 3.7% smaller) when users reached *In* than when they reached *Out* (Figure 4.8, bottom panel). However, for the other three combinations of *hand* and *side*, this effect varied considerably across users. Some users achieved much smoother movements (smaller $SPARC$) when they reached *In* than when they reached *Out*, while for other users this difference was smaller. For reaches on the right side using the right hand, a few users even tended to achieve movements that were *less smooth* (larger $SPARC$) when they reached *In* compared to when they reached *Out*.

Notably, none of the *direction* × *arm length* interaction effects reached significance (Figure 4.8, top panel). This was understandable for reaches on the left side using the right hand, since in this condition there was not much between-participant variability to explain in the first place. However, for the remaining three conditions, the smoothness benefit for reaches *In* compared to reaches *Out* was different for different participants (Figure 4.8, bottom panel). Together, these results indicated that for these three combinations of *hand* and *side*, the smoothness benefit for reaches in the *In* direction compared to reaches in the *Out* direction varied considerably across users, but this variation was not related to individual differences in arm length.

Figure 4.8: At the top, the results of the likelihood ratio tests for the effect of direction and the direction x arm length interaction for spectral arc length (SPARC). At the bottom, two different visual summaries of how the difference in SPARC between reaches in the *In* and *Out* directions varied across participants, for each combination of *hand* and *side*.

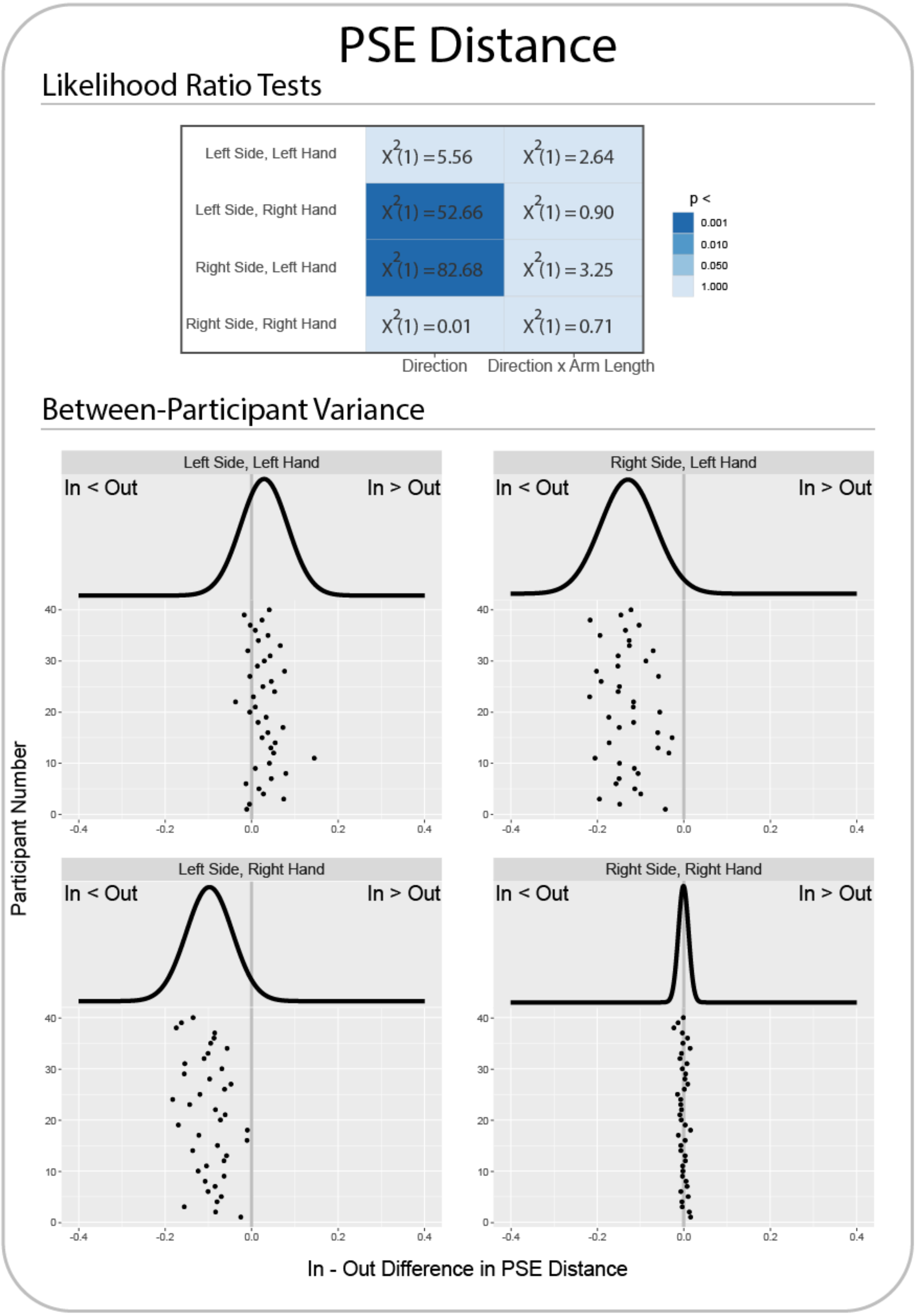


4.4.1.4 Primary Submovement Endpoint Distance (d_{PSE})

Likelihood ratio tests for the main effect of *direction* indicated that $\boldsymbol{d_{PSE}}$ was significantly different between reaches in the *In* and *Out* directions, but only for reaches that occurred on the side of the body contralateral to the reaching arm (i.e., Left Side/Right Hand or Right Side/Left Hand; Figure 4.9, top panel). This reflected the fact that, on average, users ended their primary submovements closer to the target (smaller $\boldsymbol{d_{PSE}}$) when they reached *In* than when they reached *Out*, but only for these two combinations of *hand* and *side* (Figure 4.9, bottom panel). This replicated a pattern observed in previous studies. Random effects analysis indicated that for both conditions that involved reaching on the side of the body contralateral to the reaching arm (i.e., Left Side/Right Hand or Right Side/Left Hand), the size of the difference in d_{PSE} between reaches in the *In* and *Out* directions varied considerably across users. Some users ended their primary submovements much closer to the target (smaller d_{PSE}) when reaching *In* than when reaching *Out*, while for other users this difference was much smaller.

For reaches that involved the other two combinations of *hand* and *side* (i.e., Left Side/Left Hand and Left Side/Right Hand), analysis of the fixed effect for *direction* indicated that, on average, users did not end their primary submovements significantly closer to the target (smaller $\boldsymbol{d_{PSE}}$) when they reached *In* than when they reached *Out*. For reaches on the right side using the right hand, this was because $\boldsymbol{d_{PSE}}$ was not meaningfully different between reaches in the *In* and *Out* directions for all 40 of the individual users (Figure 4.9; bottom panel). However, for reaches on the left side using the left hand, some users ended their primary submovements slightly *farther* from the target (larger $\boldsymbol{d_{PSE}}$) when they reached *In* than when they reached *Out*, while for other users $\boldsymbol{d_{PSE}}$ was not meaningfully different between reaches in the *In* and Out directions (Figure 4.9; bottom panel). As such, for reaches on the left side using the left hand, there was still between-participant variability in the size of this effect that might have been accounted for by arm length. Critically, however, none of the *direction* × *arm length* interaction effects reached significance (Figure 4.9, top panel). This indicated that, although the d_{PSE} benefit for reaches in the *In* direction compared to reaches in the *Out* direction varied considerably across users, this variation was not related to individual differences in arm length.

Figure 4.9: At the top, the results of the likelihood ratio tests for the effect of direction and the direction x arm length interaction for primary submovement endpoint distance (d_{PSE}). At the bottom, two different visual summaries of how the difference in d_{PSE} between reaches in the *In* and *Out* directions (in Unity units) varied across participants, for each combination of *hand* and *side*.

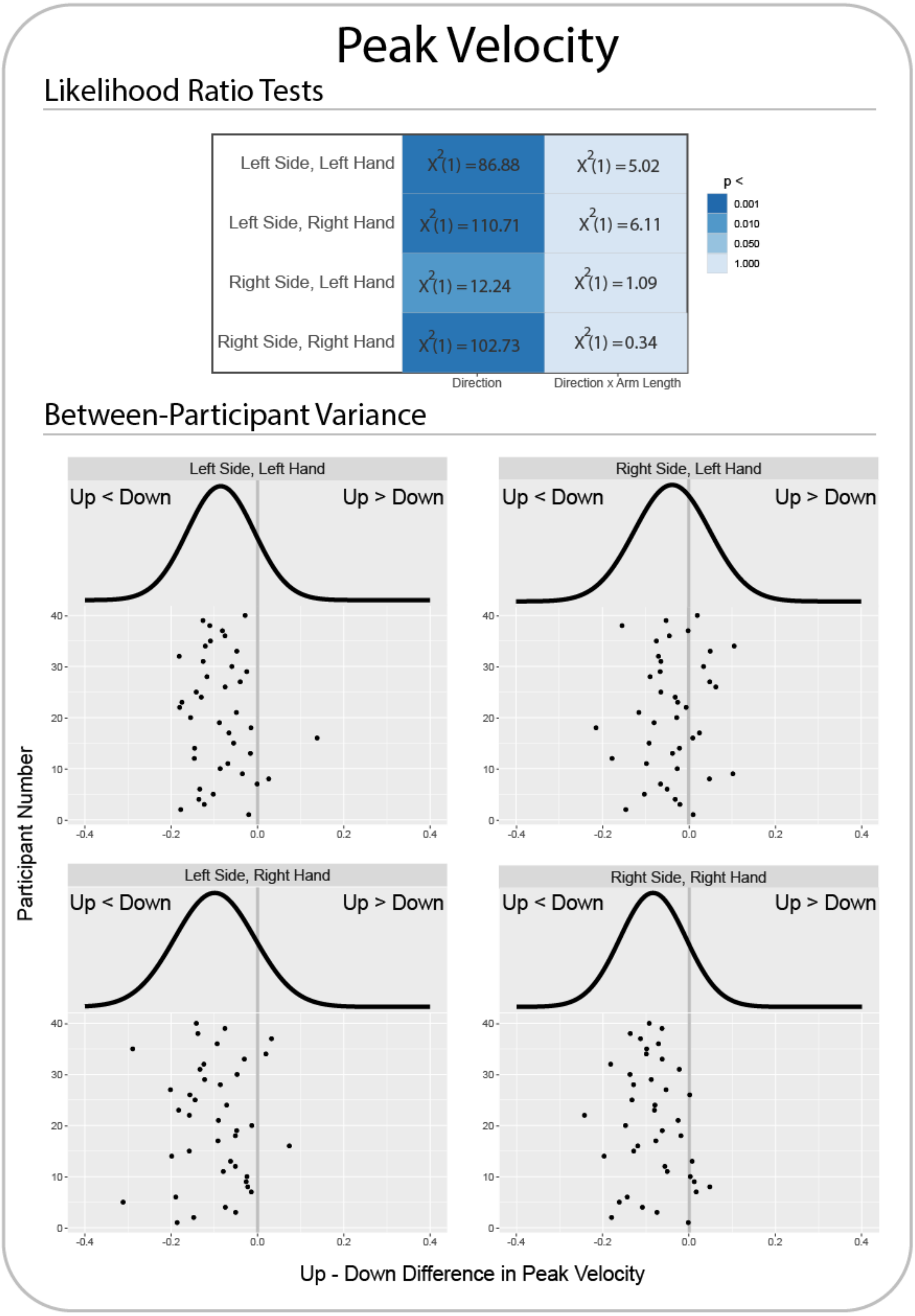


4.4.2 Differences Between the *Up* and *Down* Directions

Analysis of the fixed effects for *direction* yielded results that were consistent with our findings in Chapters 2 and 3. As in the previous studies, likelihood ratio tests indicated that $\boldsymbol{v_{peak}}$ was significantly different between reaches in the *Up* and *Down* directions (Figure 4.10, top panel). This reflected the fact that users tended to achieve slower speeds (smaller $\boldsymbol{v_{peak}}$) when they reached *Up* than when they reached *Down*. For three combinations of *hand* and *side* (i.e., Left Side/Left Hand, Left Side/Right Hand, and Right Side/Right Hand), users moved much slower on average when reaching *Up* than when reaching *Down* (Figure 4.10, bottom panel). For the remaining condition (Right Side/Left Hand), users only reached slightly slower on average when reaching *Up* than when reaching *Down*. In both the past work and the present study, $\boldsymbol{v_{peak}}$ in this condition was approximately 3.1% smaller when users reached *Up* than when they reached *Down*. However, due to the increased statistical power afforded by a larger sample size, this smaller difference reached statistical significance in the present study (Figure 4.10, top panel).

Random effects analysis revealed that for all four combinations of *hand* and *side*, this effect emerged differently for different users. Some users moved much slower (smaller $\boldsymbol{v_{peak}}$) when they reached *Up* than when they reached *Down*, while other users did not move that much slower when reaching *Up* than when reaching *Down*. A few users even moved slightly *faster* (larger $\boldsymbol{v_{peak}}$) when reaching up than when reaching down. However, notably, none of the *direction* × *arm length* interaction effects reached significance (Figure 4.10, top panel). Together, this indicated that the v_{peak} benefit for reaching *Down* compared to *Up* varied across users, but this variation was not related to individual differences in arm length.

Figure 4.10: At the top, the results of the likelihood ratio tests for the effect of direction and the direction x arm length interaction for peak velocity (v_{peak}). At the bottom, two different visual summaries of how the difference in v_{peak} between reaches in the *Up* and *Down* directions (in Unity units/s) varied across participants, for each combination of *hand* and *side*.



4.5 Intermediate Discussion

In Chapters 2 and 3, we provided a novel empirical account of how the kinematic properties of virtual hand reaches change when users reach in different *movement directions*, and how these effects can be different depending on both the *hand* used to perform movements (dominant or non-dominant) and the *side* of the body on which movements occur. In the present study, we built from these results by examining the influence of one more factor that may moderate the effects of movement direction on reaching kinematics, *arm length*. From past work in movement science, there is considerable reason to suspect that users with shorter arms may adapt to changes in movement direction differently than users with longer arms (Section 1.4.4). However, to our knowledge, no studies to-date have yet examined if and how individual differences in arm length influence the kinematic properties of virtual hand reaches. Indeed, no work to-date has examined the relationship between arm length and the kinematic properties of goal-directed reaches performed in any context, including reaches to physical targets.

In the present work, we began to address this gap by examining if and how individual differences in arm length moderate the largest effects of movement direction on reaching kinematics that we observed in the two previous studies. A sample of 40 users with a broad range of arm lengths performed the same virtual hand reaching task used in Chapter 3, and we recorded arm length measurements for each user. We addressed the following research questions:

1. Do the effects of movement direction on MT, v_{peak}, $SPARC$, and d_{PSE} for reaches on each side of the body using each hand depend on users' arm length?
2. If so, do the differences in MT, v_{peak}, $SPARC$, and d_{PSE} between reaches in different directions tend to become larger or smaller as arm length increases?

4.5.1 Summary of Findings

The results indicated that the prominent effects of *movement direction* on MT, v_{peak}, $SPARC$, and d_{PSE} that we observed in previous work replicated with the current set of participants. A few of these effects emerged consistently across all 40 participants. However, most of these effects emerged differently for different individual users. In all but one case, however, individual differences in *arm length* did not account for a significant proportion of the between-participant variation in these effects. In short, this indicated that **(1) many of the prominent effects of movement direction on reaching kinematics that we observed in previous work emerged differently for different individual users**, but **(2) for all but one of these effects, individual differences in arm length did not account for this variability**. The sole exception to this rule was the difference in MT between reaches in the *In* and *Out* directions, when users reached on the right side of their body using their left hand. This effect changed systematically as a function of *arm length*. Users with shorter arms took much less time (smaller MT) to reach *In* than to reach *Out* compared to users with longer arms; however, this difference became smaller as arm length increased. We discuss these findings in more detail below.

4.5.2 Between-Participant Variance in Effects

Random effects analysis revealed that a few of the effects of movement direction on MT, v_{peak}, $SPARC$, and d_{PSE} that we observed in the previous studies emerged consistently across all 40 participants. Specifically:

- For reaches on the left side using the left hand, all users took approximately 60 ms less time (smaller MT) to reach In than to reach Out.
- For reaches on the left side using the right hand, all but one user exhibited approximately 3.6% smaller $SPARC$ (indicating smoother movements) when they reached *In* than when they reached *Out*. For the remaining user, $SPARC$ was not meaningfully different between reaches in the In and Out directions.

However, all the other effects of movement direction on MT, v_{peak}, $SPARC$, and d_{PSE} that we observed in the previous studies emerged differently for different individual users. Practically, this meant that for reaches involving most combinations of *hand* and *side*, there were meaningful differences between users concerning (1) how much smaller MT, $SPARC$, and d_{PSE} were for reaches *In* than for reaches *Out*, (2) how much larger v_{peak} was for reaches *In* than for reaches *Out*, and (3) how much smaller v_{peak} was for reaches *Up* than for reaches *Down*. For example, for reaches on the right side of the body using the left hand, some users took much less time (smaller MT) to reach *In* than to reach *Out*, while for other users this difference was vanishingly small.

For all but one of these effects, however, individual differences in arm length did not account for a significant proportion of the between-participant variability. The sole exception was the difference in *MT* between reaches in the *In* and *Out* directions, for which individual differences in arm length did account for a significant proportion of the between-participant variability. We discuss this effect in more detail in Section 4.5.3 below. For the other effects, however, our results suggested that this between-participant variance was likely driven by a factor other than arm length. This raises a new question: **If individual differences in arm length were not responsible, what might have caused these effects to emerge differently for some users than for others?**

One possibility is that individual differences in other anthropometric characteristics that we did not examine here may have played a role. For example, users with the same arm length could differ considerably in strength or muscle mass. Together with arm length, muscle mass could also influence the inertial properties of the limb since the moment of inertia for each limb segment is a function of both length and mass. Individual differences in strength may also influence the strategies that users choose to adopt when performing reaches, since some more effortful but performant reaching strategies may be tenable for users with stronger arms but less optimal for users with weaker arms. However, to our knowledge, it is not yet clear if or how individual differences in these additional factors may influence the kinematic properties of goal-directed reaches. This should certainly be explored in future work.

Another possibility is that these effects may have emerged differently for different individual users because users assumed different limb postures while performing the reaching task. In the present task, as in typical virtual hand reaching interactions, users were free to orient their arms however they wanted while completing the task. Specifically, as long as users began each reach with the fingertip of their virtual hand at the starting position and ended each reach with their fingertip at the target position, they were free to orient the rest of their arm however they wanted before and during the movement. Past work suggests that the arm postures users adopt during reaching movements can influence how factors such as the inertial resistance of their limbs and the stiffness or “impedance” of their limbs vary as a function of movement direction in 3D space [8,133]. Therefore, it is possible that the between-participant variability we observed here may have emerged because users favored different reaching postures and then adapted their reaching behaviors differently to account for posture-dependent changes in the underlying dynamic constraints on their movements (e.g., limb inertia; [72]). This possibility could be examined in future work by systematically varying users' arm posture during the virtual hand reaching task and then exploring if certain effects of movement direction on reaching kinematics only emerge for reaches performed using specific arm postures. Past work examining the effects of limb posture on the spatial variability of reaching movements provides a blueprint for how such a study might be performed [105,145].

4.5.3 The Moderating Influence of Arm Length

Individual differences in arm length only moderated one of the effects of movement direction on reaching kinematics. Namely, for reaches on the right side of the body using the left hand, users with longer arms achieved similar overall movement efficiency (MT) when they reached *Out* or *In*. However, users with shorter arms were less efficient overall (larger MT) when they reached in the *Out* direction than when they reached in the *In* direction. This effect is summarized in Figure 4.6, which shows the predicted values of MT for reaches in each direction for hypothetical users with particularly short arms (52.3 cm) and particularly long arms (62.3 cm). These results suggest that when users begin with their left arm already reaching across their body and then reach even farther across their body to select targets in the *Out* direction, users with longer arms can achieve these movements more efficiently than users with shorter arms.

From hand kinematics alone, we cannot draw strong conclusions as to why this effect occurred. However, there are several potential explanations. One possibility is that having longer arms could enable users to complete these reaches without needing to rely as heavily on engaging their shoulders. Relying more heavily on larger muscle groups can increase execution-related neuromotor noise (e.g., [56]), which could in turn require users to spend more time performing corrective submovements to successfully reach the target (e.g., [51]). However, it is also possible that users with longer and shorter arms may tend to favor different movement strategies. These different strategies may be tailored to optimally account for properties that can vary as a function of arm length, including limb inertia (e.g., [72]; Section 1.4.1.1), gravitational torques (e.g., [65]; Section 1.4.1.4) and interaction torques (e.g., [67]; Section 1.4.1.2). Tailoring their movement strategies in this way could help users to maximize their movement performance while minimizing the effort required to complete their movements ([51,178]).

Notably, however, neither of the explanations above fully accounts for why this effect emerged for cross-body reaches using the non-dominant hand (i.e., reaches on the right side using the left hand), but not for similar reaches performed using the dominant hand (i.e., reaches on the left side using the right hand). The biomechanical requirements of reaches in these two conditions were presumably the same—in both these cases, users began with their arm already reaching across their body, and then either reached toward their body midline (*In*) or reached even farther across their body to select targets in the *Out* direction. When these reaches involved using the left hand on the right side of the body, users with longer arms achieved similar efficiency when reaching *Out* and when reaching *In*, while users with shorter arms were less efficient (smaller MT) when reaching *Out* than when reaching *In*. However, when these reaches instead involved using the right hand on the left side of the body, users with longer arms no longer enjoyed this MT benefit. Regardless of arm length, users took longer (larger MT) to reach *Out* than to reach *In*. Given that the dominant and non-dominant limbs may favor different control schemes (e.g., [162,163]), it seems reasonable that having longer arms could confer performance benefits for reaches with one arm but not for reaches with the other. However, further investigation of joint angle kinematics and underlying muscle dynamics during this reaching task would be needed to reveal precisely why this was the case.

5 LIMITATIONS, FUTURE WORK, AND IMPLICATIONS FOR RESEARCH AND PRACTICE

As the concept of the metaverse fuels a growing interest in VR and other technologies that track users' arm movements [46], virtual hand reaching will continue to be a common way for users to interact with these displays. Kinematic analysis (KA) metrics quantify different useful properties of virtual hand reaches, including the speed, efficiency, and smoothness of virtual hand reaching movements. These metrics can provide valuable insights into users' movement behaviors to support emerging uses of VR technology in several application areas, including stroke rehabilitation (e.g., [144]) and motor skills training (e.g., [1]).

Past research suggests that some KA metrics can change when users perform reaching movements in different directions (i.e., *movement direction*), and that the effect of movement direction on these metrics may be different for reaches that occur on the same or opposite side of the user's body from the reaching arm (i.e., *interaction hemispace*), for reaches performed using the dominant or non-dominant arm (i.e., *hand dominance*), and for users with longer or shorter arms (i.e., *arm length*). However, before the present work, no studies to-date had yet explored if and how all four of these factors may interact to influence the kinematic properties of virtual hand reaches.

In this dissertation, we began to address this gap by performing a series of three studies (Chapters 2-4). Having described these studies in detail in the preceding chapters, we now step back to consider this body of work as a whole. First, we briefly review the goals, methods, and principal findings for each of the three studies. We then discuss the limitations of this body of work and consider how researchers might address these limitations in future work, while also balancing the many trade-offs inherent in studying adaptations during goal-directed reaching. Finally, we discuss the implications of our findings for work in several areas at the intersection of human movement science and virtual reality. These work areas include laboratory research exploring motor control processes, predictive modeling of 3D arm movements, and emerging practical uses for kinematic analyses in the stroke rehabilitation, motor skills training, and usability evaluation spaces. For work in all these areas, our results provide valuable new insights and point to promising avenues for future work.

5.1 Review of the Present Work

In Chapter 2, we reported the results of an exploratory study that provided an initial look at how the first three factors—*movement direction*, *hand dominance*, and *interaction hemispace*— interact to influence the kinematic properties of virtual hand reaches. A sample of 20 users performed virtual hand reaches in <u>five</u> cardinal directions (up, down, left, right, or away), on both sides of their bodies, using both their dominant and non-dominant hands. The results revealed for the first time (1) that these three factors interact to influence the kinematic properties of goal-directed reaches, and (2) *how* each KA metric changes as a function of *movement direction* when users reach on either side of their body using either hand.

In Chapter 3, we then took a more detailed look at how KA metrics change as a function of movement direction for reaches performed on each side of the body using each hand. Based on our results in the first study, we focused on reaches in <u>12</u> different directions that either involved moving inward (toward the body midline) or outward (away from the body midline). As in the first study, 20 users reached in each direction on both the left and right sides of their body, using both their dominant and non-dominant hands. The results replicated our principal findings from Chapter 2 and provided a more fine-grained account of how the kinematic properties of virtual hand reaches change as a function of *movement direction* when users reach on either side of their body using either hand. In short, we found that the influence of *movement direction* on reaching kinematics is: (a) vastly different for each KA metric and (b) depends heavily on both the hand used to perform movements and the side of the body on which movements occur.

Finally, in Chapter 4, we examined if individual differences in *arm length* moderate the effects of movement direction on KA metrics, when users reach on each side of their body using each hand. A sample of 40 users with a range of different arm lengths performed the same reaching task used in Chapter 3, and the length of each user's arms was measured using standard anthropometric procedures. We then examined (a) if the largest effects of movement direction on KA metrics that we observed in previous studies emerged differently for different individual users, and (b) if these effects were systematically different for users with shorter arms than for users with longer arms. The results indicated that there were meaningful differences between users concerning how they adapted the kinematic properties of their reaches to move in different directions, for reaches on each side of their body using each hand. However, in most cases, the effects of movement direction on KA metrics were not systematically different for users with shorter arms than for users with longer arms. This indicates that between-participant variation in the effects we examined was likely caused by individual differences in factor(s) other than arm length.

Together, these three studies provide the first empirical account of how *movement direction*, *hand dominance*, *interaction hemispace*, and individual differences in *arm length* interact to influence the kinematic properties of virtual hand reaches. Indeed, to our knowledge, this represents the first time that the joint influence of these four factors on movement kinematics has been explored for goal-directed reaches performed in any context, including for reaches performed to physical targets. Our findings have practical implications for work in several areas at the intersection of movement science and virtual reality, including laboratory research on motor control processes, predictive modeling of 3D reaching movements, and the emerging use of kinematic analyses in applied contexts such as stroke rehabilitation, motor skills training, and usability assessment.

5.2 Limitations and Future Work

Like any research effort, the present work does have some limitations that are important to consider when interpreting and applying the results. Many of these limitations reflect persistent challenges and trade-offs that researchers often encounter when studying adaptations in goal-directed reaching behaviors. In the sections below, we highlight these considerations and provide recommendations for how they may be managed in future work.

5.2.1 Other Potential Moderating Factors Remain to be Explored

Given the complexity of the human motor system, there are many different factors to which users may adapt their reaching behaviors. However, in any given experiment, it is only feasible to examine how a subset of these factors influence users reaching behaviors. To isolate the effects of the selected independent variables, the other factors must be held constant. As a result, there will often be remaining questions regarding if and how the factor(s) that were held constant may moderate the effects of the selected independent variables on users' reaching behaviors. This reality was partly responsible for the research gap that we addressed in the present work: Research to-date had examined how *movement direction* influences the kinematic properties of users' reaches, but it had not yet considered if and how these effects may be different depending on the *hand* used to perform movements, the *side* of the body on which movements occur, and individual differences in users' *arm length*.

While the present work reveals for the first time how these factors interact to influence users' reaching kinematics, it is important to note that there are still other potential moderating factors that may also influence the kinematic properties of users' reaches. Specifically, we chose to focus on *movement direction*, *hand dominance*, *interaction hemispace*, and *arm length* as our independent variables because their joint influence on reaching kinematics had not yet been explored in previous research. However, to examine the influence of these four factors on reaching kinematics, we needed to hold several other factors constant. These included movement distance (0.20 units), target size (0.05 units), the height of the target array (centered at eye level), the depth of the target array (0.25 units away), and the lateral positions of the starting locations (0.25 units to the left or right of the body midline). The values for these variables were selected during pilot testing because they produced movement conditions that users are especially likely to encounter while interacting with consumer VR and XR systems (i.e., reaching to objects that are positioned near eye level within a few feet of the head). However, just as the present work explored the moderating influence of *hand dominance*, *hemispace*, and *arm length*, future work should explore if and how the variables that we held constant in the present work may moderate the effects that we observed. For example, this future work could examine if the effects of movement direction on reaching kinematics change for reaches that involve moving different distances, or when users reach to smaller or larger targets.

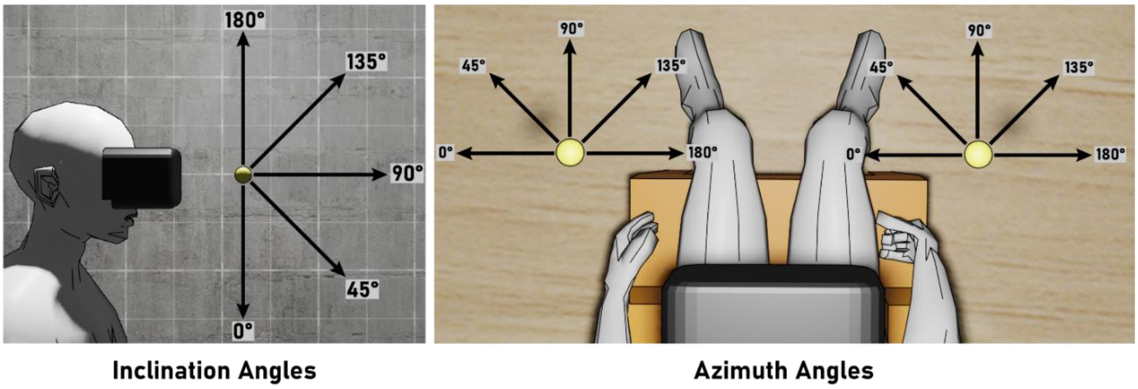
5.2.2 Other Movement Directions Remain to be Explored

Just as there is a practical upper limit on the number of independent variables that can be considered in any given experiment, there is also often a limit on the number of levels that a researcher can examine for a particular independent variable. This constraint was particularly important for examining the effects of *movement direction* on reaching kinematics, since users can move in an infinite number of potential directions from any given starting position but there is a practical limit on the number of movement directions that can be considered in any given experiment.

In the present work, the practical limit on the number of movement directions that we could consider arose from the need to model movement direction as a factor. This approach provided the flexibility needed for exploratory analysis, since it did not require us to make any assumptions about how each kinematic metric varied as a function of movement direction. However, this flexibility came at the cost of increasing the complexity of our multilevel linear models, since including n movement directions required us to estimate slope parameters for $4(n-1)$ dummy variables. As a result, considering too many movement directions in each analysis (in our case, more than 12) could have led to overfitting. Therefore, in each study, we focused our attention on reaches that involved specific sets of movement directions. Additional work should explore if and how the kinematic properties of goal-directed reaches vary across movement directions other than those that we examined here.

In future work exploring the influence of movement direction on reaching kinematics, there are other measures that researchers might consider taking to consider an even larger number of movement directions in a single study. First, to examine a larger set of movement directions and still benefit from the flexibility that comes with modeling movement direction as a factor, without increasing the risk of overfitting models, researchers might first consider collecting even larger datasets. However, this may be difficult in practice given the time and resource costs associated with collecting data from larger numbers of participants. Alternatively, researchers might consider modeling the effect of movement direction on reaching kinematics using an approach that makes more assumptions but consumes fewer degrees of freedom in their models. For example, researchers might quantify the movement direction for each target using an inclination angle and an azimuth angle (Figure 5.1), and then test for linear relationships between these two variables and each kinematic metric (e.g., [37]). We chose not to use this approach in the present work, because it would only enable us to capture effects of movement direction on reaching kinematics that followed a specific pattern. Specifically, this approach would require us to assume that the values of each KA metric would either increase or decrease linearly as inclination and/or azimuth angle increased. Based on past work, there was no valid reason to think that this was the only way that reaching kinematics might change as a function of movement direction. However, depending on the goals of future work, other researchers may be willing to make these types of assumptions in exchange for the opportunity to examine an even larger number of movement directions in their analyses.

Figure 5.1: An illustration of how a hypothetical set of movement directions could be quantified using inclination angles (left) and azimuth angles (right).



5.2.3 Considerations for Future Qualitative Analyses

Since the present work was exploratory, we were constrained by the need to examine if the values of each KA metric varied *significantly* across the different movement directions. This was critical for understanding if the direction-dependent changes in each metric that we observed were larger than what we would expect to see purely by chance. However, in some future work, researchers might instead be more interested in exploring *qualitative* trends concerning how a given kinematic metric changes across reaches in different movement directions. For example, researchers may be interested in understanding how a kinematic metric that is useful in a specific applied context (e.g., $SPARC$ for monitoring arm function recovery; [17,94]) varies across an arbitrary set of movement directions, to enable more precise comparisons between KA metrics for reaches in those different directions.

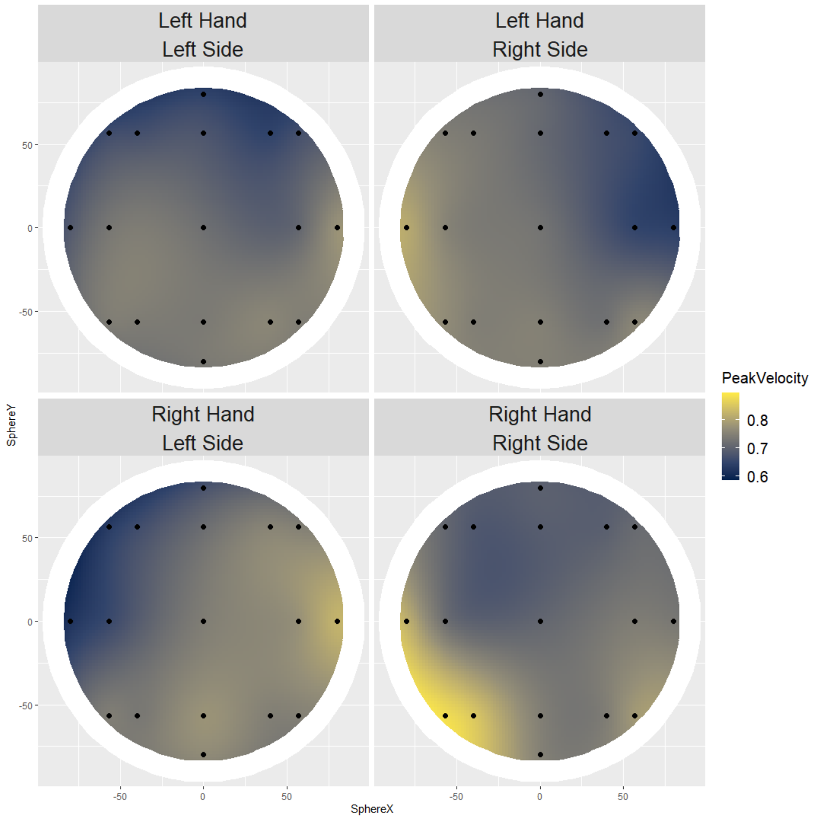
In theory, these types of qualitative analyses could examine any number of movement directions without needing to manage the constraints imposed by the need to fit statistical models (e.g., Section 5.2.2). However, even for these studies, it still might not be practical to examine enough movement directions to provide a full, high-resolution account of how a given kinematic metric changes as a function of movement direction. Indeed, to achieve this, a researcher might need to examine reaches in hundreds of different directions. This would dramatically increase the amount of time required to collect data and would likely exhaust participants.

One possible way to circumvent these constraints in future qualitative analyses might be to (1) examine a relatively large number of movement directions and then (2) interpolate the values of each metric for the movement directions that fall between the ones examined in the study. Such an approach could enable researchers to provide a high-resolution picture of how a given kinematic metric changes as a function of movement direction while collecting data from a more manageable number of movement directions. It could also enable researchers to produce novel visualizations like Figure 5.2 below, which could be useful for helping analysts to understand how a given metric changes more continuously across different movement directions. However, it is not yet clear which interpolation approaches may be most appropriate for this type of work, and this would need to be explored in future work.

As a starting point, it may be particularly useful to consider the various interpolation techniques that have been used to create scalp maps for EEG research. These techniques can be used to estimate how voltage changes across different locations on a user's scalp, but it may also be possible to adapt them to estimate how KA metrics change across different movement directions. More specifically, spatial interpolation approaches for EEG data can provide a more continuous estimate of how electrical activity changes across a user's scalp, based on measurements captured at a limited set of electrode sites. Exploring the relationship between movement direction and reaching kinematics seems to involve a roughly analogous problem: Providing a more continuous estimate of how a

KA metric changes across the full range of possible movement directions, based on measurements captured for a limited set of movement directions.

Figure 5.2: Heatmaps showing interpolated estimates of how peak velocity changed as a function of movement direction for reaches on each side of the body, using each hand. The values for this plot were obtained by applying biharmonic spline interpolation (as implemented in the eegUtils package in R) to the peak velocity values for 17 movement directions, using the data collected for Chapter 3.



5.2.4 Other Kinematic Metrics Remain to be Explored

In the present work, we focused on exploring how a set of six kinematic metrics changed as a function of *movement direction*, *hand dominance*, *interaction hemispace*, and *arm length*. We chose to focus on these metrics because past work suggested that they may be particularly sensitive to these four factors. However, there are many other kinematic metrics that we did not examine in the present work, but which can also quantify useful aspects of users' movement behaviors (see e.g., [169]). In addition, as KA metrics continue to be used in more application areas, new metrics will likely be developed to index the properties of users' movement behaviors that are particularly important for those applications. As such, additional work will be needed to examine if and how these other kinematic metrics may vary as a function of movement direction and the other factors that we examined here. Forthcoming work from our laboratory will continue to address this need, and the datasets we collected for the present work will make it possible to perform these future investigations without needing to collect additional data.

5.2.5 Future Work Should Examine Other User Populations.

In the present work, we focused on a particular segment of the user population: right-handed users who were relatively young. Our results provided valuable new insights into how this large segment of the general population adapts the kinematic properties of their virtual hand reaches to move in different directions, and how these direction-dependent kinematic adaptations emerge differently depending on the hand used to perform movements, the side of the body on which movements occur, and individual differences in users' arm length. However, as in any research, care should be taken when generalizing the results beyond the specific population from which the sample of participants was drawn. Our findings here may or may not emerge similarly for left-handed users or for older users who fall outside the age range that we examined in the present work.

First, in the present work, we focused exclusively on participants who were strongly right-hand dominant, with scores of at least 40 on the Edinburgh Handedness Inventory (M = 81.4, SD = 14.8, min = 41.2, max = 100; [138]). This decision was motivated by past findings which indicated that the influence of hand dominance on reaching kinematics may be different for left handers than for right handers. Specifically, there is evidence that interlimb differences in reaching kinematics may be less pronounced for left-handers than for right-handers [136,150], possibly because left-handers may use their non-dominant arm more in daily life due to the environmental pressures of living in a predominantly right-handed world. These findings suggest that it may not be appropriate to simply treat left-handers as "reversed right-handers" [136], but that separate investigations would likely be necessary to examine how hand dominance moderates the influence of movement direction on reaching kinematics for left- and right-handers. As such, we chose to focus here on the larger of the two groups, as right-handers tend to make up approximately 85-90% of the general population [118]. Additional work will be needed to explore the extent to which our findings here emerge similarly for left-handed users.

Second, in the present work, we focused on participants who were relatively young (mean age = 23.14, *SD* = 4.97, *min* = 18, *max* = 44). Focusing on this group enabled us to quantify how healthy young individuals adapt the kinematic properties of their virtual hand reaches, in the absence of any motor impairments (e.g., hemiparesis; [183]) or changes in movement strategies that can emerge as individuals age (e.g., [21,64,69,96]). However, since users' movement strategies can change with age, our findings here may or may not generalize to individuals who fall outside the age range that we examined in the present work. Additional work will be needed to explore if and how the joint influence of movement direction, hand dominance, interaction hemispace, and arm length on reaching kinematics may be different for older users. For these purposes, a multilevel modeling approach like that employed in Chapter 4 could be used to explore if and how users' age may moderate the effects of these factors on reaching kinematics.

5.2.6 Generalization to Other Reaching Tasks

In the present work, we focused on examining how movement direction and the three moderating factors influence the kinematic properties of unconstrained, discrete, point-to-point 3D reaching movements performed in VR (i.e., "virtual hand reaches"). However, movement science researchers may need to consider the extent to which our findings in the present work may generalize to other tasks that have also been used for research in this space. These other tasks include reciprocal pointing between two virtual targets (e.g., [14,114]), 3D reaches to physical targets (e.g., [21,24,34,97,193]), 2D reaches where the hand is constrained to the horizontal plane (e.g., [22,176,187]), reaches performed without visual feedback of the hand (e.g., [173,179]), and several other task contexts (e.g., [63,142,174]). In a similar vein, future practitioners may also need to consider if the present results can be expected to generalize to movements performed in specific applied contexts. This could include stroke assessment tasks that simulate an activity of daily living (e.g., [131,132,141]) or training tasks that simulate performance of a particular motor skill (e.g., [23,31,129]). As such, it is important to explicitly consider what factors may influence the likelihood that our results in the present work will generalize to any given movement task.

In short, we suspect that our findings in the present work would be most likely to generalize to other tasks in which the physical and perceptual constraints on users' reaches are as similar as possible to those present during our studies. In other words, the more similar a given movement task is to the task that we examined here, the more likely it is that the present results will generalize to that other task. This is largely because the human motor system is highly adaptive, such that users can employ different movement strategies to maximize performance and minimize effort when they are faced with different environmental constraints (e.g., [51,178]). Consequently, as reaching tasks become more different from each other in terms of (a) how they define success (i.e., goals), (b) the information available to inform users' movements, and/or (c) the underlying dynamic factors that constrain users' movements while they perform the task (e.g., gravitational and interaction torques; [65,161]), it becomes less likely that users' reaches in those task contexts will exhibit similar kinematic characteristics.

Using these criteria, we suspect that our results in the present work would be most likely to generalize to virtual hand reaches performed using different VR devices or simulations, and slightly less likely to generalize to unconstrained 3D reaches performed to physical targets. For reaches performed using other VR devices or simulations, both the physical constraints on users' movements and the perceptual information available to inform their movements should be largely similar to the conditions in the present study. Consequently, we would expect our findings in the present work to generalize to many VR-based reaching tasks, particularly when the goals and constraints of these tasks are similar to those involved in the present study. For 3D reaches to physical targets, the physical constraints on users' movements may be mostly similar to those present during virtual hand reaching, but the perceptual information available to inform users' movements may be different from the conditions in the present study. This is partly because, due to more limited depth cues and display limitations such as limited field of view, depth estimation can sometimes be less accurate in VR environments than in the real world [156,185], and users may adopt different movement strategies to account for these deficiencies (e.g., [14,40,114]). Consequently, although our results may still generalize to 3D reaches performed to physical targets, we cannot be perfectly certain that all the patterns we observed in the present work will also emerge for reaches performed in this other task context.

Comparatively, we suspect that our results in the present work would be much less likely to generalize to reaching tasks that introduce goals or constraints on users' reaching behaviors that are very different from those involved in unconstrained virtual hand reaching. This includes 2D reaches where the user's hand is constrained to the horizontal plane (e.g., [22,176,187]), reaches performed without visual feedback of the hand (e.g., [173,179]), and reciprocal pointing that involves repeatedly moving between a pair of targets (e.g., [14,74,114]). However, considering the growing popularity of VR technology and the potential value of using KA techniques to quantify users' movement behaviors in VR, there may be more value in considering how findings generalize from these contexts to virtual hand reaching, rather than the other way around. This would involve answering a different question: To what extent do kinematic differences observed for reaching tasks in these more disparate contexts (e.g., 2D reaches in the horizontal plane) also emerge for virtual hand reaching movements? Understanding this might make it possible to leverage some of the extensive research examining these other task contexts to make predictions about how users will behave in VR environments.

5.2.7 Future Work Should Examine Both Kinematics and Dynamics

Finally, the present work revealed for the first time precisely *how* the KA metrics we examined changed when users performed virtual hand reaches in different directions, and how these effects of movement direction were different depending on the hand used to perform movements, the side of the body on which movements occurred, and individual differences in users' arm length. However, additional work will be needed to examine *why* these properties influence each kinematic metric the way they do. For example, *why* do users exhibit smaller MT and larger v_{peak} when reaching inward than when reaching outward? This pattern could reflect a specialized strategic adaptation, an artefact of direction-dependent differences in limb inertia, or perhaps something else entirely.

To explore this next set of questions, future work should consider co-registering hand kinematics with motion tracking of the limb segments and EMG of the chest, shoulder, and arm muscles. Examining these additional measures could provide an even more detailed picture of the limb movements and muscle activity that are responsible for the patterns of hand kinematics that we observed here. This would make it possible to distinguish between the many possible explanations for the effects we observed here.

5.3 Practical Implications

Our findings in the present work have practical implications for several research and design efforts at the intersection of movement science and virtual reality. For laboratory research examining the kinematic properties of goal-directed reaches, our results provide new observations to be accounted for by existing theory, reveal new research needs, and highlight the potential value of VR systems as an experimental platform for studying goal-directed reaching. For modeling work aimed at predicting 3D reaching performance in VR, our results suggest that the relationship between movement direction and MT may be too complex to be captured by predictive models based on Fitts' law (Fitts, 1945). Rather, more complex models like those based on optimal feedback control theory (Todorov & Jordan, 2002) may be more appropriate for predicting MT for 3D reaching tasks. Finally, our results provide a deeper understanding of how users adapt their movement behaviors that can be used to interpret kinematic measures more precisely in several emerging application areas, including stroke rehabilitation and motor skills training. However, additional work will be needed to maximize the value that future researchers and practitioners can glean from kinematic measures in these contexts. We discuss these implications in greater detail in the sections below.

5.3.1 Implications for the Applied Use of Kinematic Analyses

First, our results have implications for applied work in several fields where kinematic analyses of 3D reaching movements performed in VR can provide useful insights into users' movement behaviors. In the sections below, we review these application areas and provide a summary of how KA metrics captured in VR can provide value for work in each of these areas. We then provide some suggestions for how researchers and practitioners should approach using KA metrics to quantify users' reaching behaviors in these emerging application areas.

5.3.1.1 Recall: KA Metrics Captured in VR Show Promise in Several Emerging Application Areas.

First, recall that kinematic analyses of 3D reaches performed in VR may soon be able to provide insights for monitoring arm function recovery in stroke patients. In this space, VR has shown promise as a tool for delivering therapy to restore arm function in stroke patients [47,80,119,127]. At the same time, there has also been a growing trend toward using KA metrics to monitor arm function recovery, by analyzing movement data captured while patients perform various types of reaching movements [103,130,169]. Given these two parallel developments, there is reason to think that VR systems could eventually be used to both deliver stroke rehabilitation programs [144] and administer kinematic assessments to monitor patients' progress [92] as part of future VR-based telerehabilitation programs [98,144,164,184].

Second, KA measures could also soon be used to monitor learners' progress during VR-based motor skills training, especially for tasks such as assembly that rely heavily on goal-directed reaching movements. In recent years, VR has shown promise as a means of administering training to improve workers' performance on psychomotor tasks across a range of different domains [1], particularly in the healthcare and manufacturing sectors [153]. Applications to-date have included VR-based training for assembly tasks (e.g., [23,31,129]), surgical tasks [134,151], and welding [175]. When the skills being trained in these contexts involve goal-directed reaching movements, traditional KA measures could be useful for measuring students' performance on different aspects of the task. This could be used to track students' improvement over time, or to help instructors zero in on the elements of a task that are still giving students the most trouble.

Third, and most speculatively, KA measures could also soon be used to identify usability issues that emerge when users reach to interact with objects at different locations in virtual environments. These metrics could help to highlight specific tasks or portions of an interface that are giving users the most trouble, so that designers can investigate these issues further and adjust the interface as needed. This approach could also be used to identify usability issues during reaching interactions with other types of 3D interfaces, including those presented using future AR systems. Unfortunately, work to-date on this topic has been relatively sparse. However, there is some initial evidence that kinematic measures can be useful for identifying when users have trouble selecting interface elements in a VR environment [38,93]. As highlighted in our studies, KA metrics that index several meaningful aspects of users' movement behaviors can be calculated using the data that VR systems already collect. This suggests that automated usability analyses may be a promising future use case for kinematic analyses.

5.3.1.2 Future Analyses Should Consider the Fact that Many KA Metrics are Direction-Dependent.

Our results in the present work highlight one key limitation of KA metrics that researchers should consider when using KA metrics in these emerging application areas. In short, our findings confirmed that the KA metrics we examined here are direction dependent, meaning that they can assume different values for reaches in different directions. Furthermore, the relationship between movement direction and several KA metrics can be (1) different depending on both the hand used to perform movements and the side of the body on which movements occur (Chapters 2-3), and (2) vary considerably across different individual users (Chapter 4). Researchers may need to account for this when interpreting KA metrics in future applied contexts, especially when they need to compare kinematic results between reaches that involve moving in different directions. For example, a future stroke researcher might need to examine KA metrics for movements in different directions to determine if a patient has difficulty moving in some directions but not others. Similarly, an instructor using VR-based training might need to examine KA metrics for the different movements that make up an assembly task to identify which parts of the task that are giving their student the most trouble.

In these cases, researchers may benefit from collecting baseline data for the movement tasks they plan to examine. This can enable researchers to understand how the KA metrics in which they are interested change when users adapt their behaviors to the different movement conditions examined in their task, *when the phenomenon of interest for their research (e.g., motor impairment) is not present*, and if these direction-dependent changes are large enough to meaningfully influence their results. If the KA metrics of interest do not vary meaningfully across the different reaching conditions, then researchers can be more confident that any differences between those conditions reflect differences in the underlying phenomenon in which they are interested (e.g., motor impairment) rather than typical patterns of direction-dependent adaptation. However, if the KA metrics of interest do vary meaningfully across the different reaching conditions, then there are at least two courses of action that researchers might consider.

5.3.1.2.1 Potential Approach: Compare Kinematic Results to a Baseline

Especially if an analysis involves examining trends that emerge across a group of users, researchers may be able to use baseline data from their task to distinguish between (a) direction-dependent changes in each KA metric that are related to the phenomenon of interest (e.g., motor impairment) and (b) direction-dependent changes in each KA metric that emerge even when that phenomenon is not present. For example, after collecting baseline data for a new reaching task, a stroke researcher might find that the *spectral arc length* ($SPARC$) metric is 0.5 larger in condition A than in condition B when healthy participants perform the task. If they observe a difference of the same size in the kinematic results from stroke patients, they would then be able to tell that this difference reflects a typical pattern of adaptation rather than a stroke-related motor deficit.

Unfortunately, this approach might be more difficult to implement for analyses that involve examining kinematic results for an individual user. These types of analyses could be especially common in stroke rehabilitation settings, where analysts may need to analyze kinematic results from individual patients. For these analyses, researchers may need to consider that the baseline of “typical” direction-dependent changes in KA metrics may be different for different individual users depending on various anthropometric and/or psychological characteristics. This concern arises from our results in Chapter 4, where we found that in some cases the effects of movement direction on KA metrics can be considerably different for different individual users.

In theory, researchers might be able to account for this by first examining if direction-dependent changes in a KA metric are meaningfully different across individual users in their baseline data. If any direction-dependent changes in a KA metric are similar for all users, then researchers could confidently use the average patterns of direction-dependent change to interpret their results (as described above). Comparatively, if any direction-dependent changes in a KA metric are meaningfully different for different individual users, then researchers might instead need to establish a separate baseline for each individual user. In theory, this could be accomplished by (a) identifying what properties of users influence how they adapt their reaching behaviors during the task (e.g., anthropometric characteristics), (b) quantifying how each of the relevant properties moderate the relationship between movement direction and the KA metric, and (c) using the resulting model to estimate the “typical” pattern of direction-dependent changes in a KA metric for a given individual, given how they score on each of the relevant properties (e.g., anthropometric characteristics). In practice, however, such an approach would likely be prohibitively expensive and would introduce additional methodological complexity. It would also hinge entirely on the researchers’ ability to produce an accurate predictive model of typical reaching adaptations, which could be a very difficult task in and of itself.

5.3.1.2.2 Potential Approach: Develop KA Metrics that are Less Sensitive to Movement Direction

Considering the difficulties that may be involved in compensating for direction-dependence in KA metrics, especially when analyzing kinematic results for individual users, it may instead be useful to circumvent these difficulties entirely. To this end, researchers might instead focus on finding or developing KA metrics that both: (1) index the movement properties of interest for their work (e.g., speed, efficiency, smoothness) and (2) do not change meaningfully as users adapt their movement behaviors to reach in different directions. As we discussed above, the definition of what constitutes a "meaningful" amount of direction-dependent change for a given KA metric would likely depend on the context and the size of the effects in which researchers are interested. The goal would be to find metrics for which the "noise" introduced by direction-dependent changes in the metric is small enough that it does not meaningfully influence the effects of interest in a given study.

Additional work will be needed to either find or develop KA metrics that meet these criteria for each emerging application area. However, especially for researchers in the stroke rehabilitation space, it may be useful to begin by considering KA metrics that are derived using submovement decomposition algorithms (e.g., [159]). There is already some evidence that these metrics can index arm function recovery in stroke patients [158], and preliminary results from our laboratory suggest that some of these metrics may be relatively consistent across reaches in different directions. These metrics can be computationally expensive, which may account for why they have not been used as widely in the motor control and stroke rehabilitation literature. However, if more efficient submovement decomposition algorithms emerge in the coming years, then KA metrics derived using this approach could be particularly useful tools for quantifying arm function recovery in stroke patients. Future work from our laboratory will explore the potential of these metrics in greater detail.

5.3.2 Implications for Improving Predictive Models of Reaching Performance

Our results also have implications for improving predictive models of human movement performance, which aim to predict the *movement time* (MT) for any given reaching task based on specific properties of that task. For several decades, researchers and practitioners have relied on performance models based on Fitts' law [62] to predict MT for pointing interactions with 2D computer interfaces. These models predict MT for a given reach based on two task properties: The distance the user's hand must travel to reach the target (movement distance; D) and the size of the target to which they are reaching (target size; S). Fitts' law models capture the influence of these task properties in a single term known as the *index of difficulty* (ID), and they predict MT by fitting a linear model that includes ID as a predictor. For example, a common formulation for a predictive model based on Fitts' law is

$$MT = a + b\log_2\left(\frac{2D}{S}\right)$$

where $\log_2\left(\frac{2D}{S}\right)$ is the index of difficulty, and a and b are coefficients derived through linear regression. Although there are several different formulations, models based on Fitts' law generally predict that users will take longer to reach targets that are smaller and/or farther away from the starting position.

Models based on Fitts' law have been found to predict users' movement performance very accurately for interactions with 2D user interfaces (e.g., [2,115]). As a result, researchers and practitioners have been able to rely on these models to inform the design and testing of 2D user interfaces (e.g., [87]). However, models based on Fitts' law have been found to be much less effective at predicting movement performance for 3D reaches (e.g., [34,37,128,180], but see [114]). While Fitts' law models regularly account for more than 90% of the variance in MT for 2D reaches (e.g., [115]), the same models can sometimes account for as little as 50 - 70% of the variance in MT for 3D reaches (e.g., [34,37]). One likely explanation for this drop off in performance is that factors other than target size and movement distance may exert a larger influence on how users perform 3D reaches.

Our results in the present work confirmed this suspicion, at least for the discrete 3D reaching task that we examined here. Specifically, we found that when target size and movement distance are held constant, MT varied considerably across reaches in different directions. This sheds some light on why Fitts' law models, which do not consider the effects of movement direction on MT, may not accurately predict MT for these types of 3D reaching movements. However, critically, we also found that the influence of movement direction on MT was highly context dependent. Specifically, the relationship between movement direction and MT depended on both the hand used to perform movements and the side of the body on which movements occurred. Further complicating the situation, we also found that this relationship could emerge differently for different individual users. While simple extensions to traditional Fitts' law models might be able to account for the influence of movement direction on MT if this influence were consistent across different contexts and users, our present results suggest that this may not always be the case. As such, for predictive models to account for the complex, context-dependent ways that MT varies across 3D reaches in different directions, we may need to do more than simply add new terms to relatively simple models based on Fitts' law (e.g., [34,37,114,128]). Rather, we may need to rely on more complex and flexible modeling frameworks to account for these complex relationships between movement direction and MT.

For this purpose, computational modeling frameworks based on optimal feedback control theory (OFCT; [45,178]) may provide one useful way forward. In short, OFCT assumes that the motor system minimizes a cost function that accounts for both the goals of a reaching task and the effort costs associated with moving. This logic is built into a feedback control policy that determines the next motor command in the sequence for a given movement, based on incoming perceptual information about the current state of the body. See [45] and [60] for detailed summaries of this approach. Computational models based on OFCT are considerably more complex than models based on Fitts' law. However, OFCT models may be able to provide the flexibility needed to predict MT for 3D reaches across different task contexts. These models may also be able to account for how individual differences in psychological or biomechanical characteristics may influence users' reaching behaviors by incorporating these factors into the cost function for each user. Conveniently, modeling approaches based on OFCT have already begun to make inroads into the HCI community [60]. Our results in the present work suggest that researchers who are interested in accurately predicting movement performance for 3D reaches should consider adopting these modeling approaches for their future work.

5.3.3 Implications for Research on Goal-Directed Reaching Behaviors

5.3.3.1 Our Results Provide New Observations to Be Explored in Theoretical Work

In the present work, we examined the kinematic properties of goal-directed reaches in conditions that have not yet been explored in previous work. Specifically, to our knowledge, no studies to-date have yet examined how the kinematic properties of goal-directed reaches change as a function of movement direction for reaches performed on both sides of the body using both hands. As a result, our findings here provide new observations that can contribute to the continued development and refinement of theories related to human motor control.

Specifically, we suspect that our findings may be especially relevant for work related to the multiple process model of goal-directed reaching (e.g., [51,55]) and the dynamic dominance hypothesis for motor lateralization (e.g., [162,163]). The former model may be able to account for some of our observations concerning how d_{PSE} changes as a function of movement direction for each combination of hand and side, while the latter may be able to account for patterns of movement kinematics that only emerged for reaches involving one of the two arms. The bodies of work behind each of these theories are extensive and nuanced, and detailed speculation as to how the present results may relate to each theory is beyond the scope of the present work. However, researchers who specialize in testing and developing these theories are encouraged to consider the extent to which the new observations of reaching behaviors that we provide here may or may not be accounted for by existing theory. The datasets collected for the present work will be available upon request to aid these types of investigations.

5.3.3.2 Future Work Should Explore How Individual Differences Influence Goal-Directed Reaching Kinematics.

Most of the past work examining how users adapt their reaching kinematics to differences in movement direction or other factors (e.g., hand dominance, interaction hemispace) has focused on trends that emerge in the aggregate, when data are averaged across a group of users. However, in Chapter 4, we found evidence that the effects of movement direction on reaching kinematics for reaches on each side of the body using each hand can sometimes be considerably different across users. For example, we found that when users reached on the right side of their body using their left hand, some users exhibited much smaller *MT* when reaching in the *In* direction than when reaching in the *Out* direction, while for other users this difference was much smaller. We observed similar findings for several other metrics, and for reaches that involved the other combinations of *hand* and *side*. Collectively, these findings suggest that the effect of movement direction on reaching kinematics for reaches on each side of the body using each hand may not always be the same for all users. Rather, some users may adapt their reaching behaviors differently than others, possibly because of individual differences in anthropometric characteristics (e.g., arm length) or the types of movement strategies that they tend to favor. As such, there may be value in looking beyond trends that emerge in the aggregate to explore how different individual users adapt their reaching behaviors to move in different directions.

Specifically, past research in movement science has revealed several patterns concerning how the kinematic properties of reaching movements change when users reach in different directions (See Section 1.5.1 for a summary). In some cases, these observations have provided critical evidence to inform the development of prominent motor control theories (e.g., [113]). Given that many of the largest direction-dependent changes in reaching kinematics that we observed in the present work varied considerably across participants, it is possible that the patterns observed in these past studies may emerge differently for different individual participants as well. As such, future research should consider re-examining established direction-dependent patterns of reaching kinematics through the lens of individual differences.

On the one hand, this work may reveal that direction-dependent adaptation patterns that have been observed in the aggregate emerge similarly for each individual user. This would indicate that these adaptation patterns are common to all users and are not influenced by individual differences. On the other hand, this work might instead reveal that some individual users adapt their reaching behaviors differently than others. Such between-participant variation could be caused by individual differences in any number of factors, including anthropometric, biomechanical, or psychological characteristics. Importantly, by examining any between-participant variance rather than averaging across it, researchers could reveal if and how individual differences in these factors may influence how users adapt their reaching behaviors. For example, do users with greater strength or larger muscle mass adapt their reaching strategies differently when they encounter the additional effort costs associated with overshooting a target when moving downward compared to upward [113,139]? For motor control theory, this work could reveal if and how the physical and/or psychological properties of individual users may influence how they plan and perform their reaching movements. To our knowledge, this topic has not yet been heavily explored in the motor control literature.

To address these questions, researchers will need to explore how the effects of variables that are manipulated or measured for each trial (e.g., *movement direction*, *hand*, *side*) depend on individual difference variables that are measured for each participant (e.g., arm length). The present work (Chapter 4) provides an example of how this can be achieved. Namely, multilevel linear modeling [104] can provide a useful solution to this challenge. This approach has not been used extensively in work studying goal-directed reaching movements, but it has become much more accessible in recent years with the release of software implementations such as the lme4 package in R [13]. As multilevel modeling techniques continue to improve, it will likely become even easier to study if and how individual difference characteristics influence how users adapt their reaching behaviors.

5.3.3.3 VR Systems Show Potential as an Experimental Platform for Studying Goal-Directed Reaches.

More generally, our experience performing the present work has led us to believe that virtual reality shows considerable promise as a future platform for studying reaching behaviors and other human arm movements. In the long term, performing reaching studies in VR could offer several benefits, compared to studying reaches performed to physical targets. First, VR systems can give researchers complete control over a participant's visual environment. This new level of flexibility could be used to explore how users plan and complete reaching behaviors in specific environmental contexts by simulating those contexts in the laboratory. Second, for reaching tasks in VR, researchers could easily position targets at any desired location in 3D space. This could help to eliminate many of the practical difficulties involved with making targets appear and disappear at different locations in 3D space, which researchers have addressed in the past using creative workarounds (e.g., [34,114]). Finally, most consumer VR systems already collect the motion tracking data needed to perform many kinematic analyses, and systems like the Meta Quest can use inside-out tracking to collect these data without requiring additional external sensors. As such, VR systems could also provide a flexible, low-cost means of collecting kinematic data for studies examining human reaching behaviors.

However, it is important to note that several technical limitations of VR technology will likely need to be addressed before researchers could use VR-based reaching tasks interchangeably with real-world reaching tasks. First, the sampling rate and spatial precision of the kinematic data from current consumer VR systems is not yet equivalent to what can be achieved with specialized optoelectronic motion tracking systems (e.g., [79]). However, as consumer VR systems become more and more advanced, the performance gap between these technologies will likely continue to close. Second, there is evidence that stereo display deficiencies in current VR systems may cause users to move differently in VR than they would in the real world [14,114]. As such, the results of reaching studies using current VR technologies may or may not generalize perfectly to reaches performed in the real world. However, as display technologies continue to improve, the perceptual differences between VR environments and the real world may continue to shrink [95,110,111,125]. As such, it may eventually be possible for researchers to use reaching studies implemented in VR interchangeably with studies implemented in the real world. This envisioned future may not be here yet, but researchers should be ready if and when it arrives.

5.4 Closing Thoughts: Working Toward a Promising Future for the Kinematic Analysis of 3D Reaches

More than 120 years ago, R.S. Woodworth [192] first examined the kinematic properties of goal-directed reaches by studying the movements of a handheld pencil on paper. In the decades since, researchers have used kinematic analysis (KA) techniques in the laboratory to answer important questions about the planning and control of reaching movements (e.g., [36,51–53,113,176]), using motion data captured with specialized optoelectronic motion tracking equipment. KA metrics have been an exceptionally valuable tool in this space, making it possible for researchers to look beyond users' overall performance on a reaching task (e.g., accuracy or completion time) to understand *how* the motor system adapts to achieve a given level of performance.

As VR, AR, and other immersive 3D display systems that can track users' arm movements become more widely available to consumers, human arm movement data will become much more readily available. In short, what used to require a movement science laboratory is increasingly being built into the average consumer's gaming equipment. This introduces some exciting opportunities to take KA techniques outside of the laboratory to solve real-world problems and to provide insights into users' movement behaviors in more naturalistic settings. As we have discussed above, researchers have already recognized the potential of KA metrics for assessing arm function in stroke patients (e.g., [103]), and the parallel emergence of VR-based rehabilitation programs (e.g., [144]) suggests that VR-based kinematic assessments for stroke patients may not be too far off. There are also promising potential uses of KA metrics in other application areas, including motor skills training (e.g., [1]) and automated usability assessments (e.g., [93]), although these potential applications have not yet received as much attention. In the long term, as arm movement data from millions of users becomes more readily available and organizations work to extract value from these data in new and creative ways, KA metrics may prove useful in ways that we cannot yet envision.

Our findings in the present work remind us that, as we move toward this exciting future, it will be important to understand the limitations of KA metrics. This understanding will enable researchers to compensate for the limitations of existing KA metrics and, where necessary, spur work to develop new KA metrics that provide similar insights with fewer limitations. The present work contributes in a meaningful way to this task by exploring one key limitation of KA metrics: the fact that they can be sensitive to various properties of a reaching task (e.g., movement direction). Specifically, our work:

- Revealed for the first time that the effect of movement direction on several commonly-used KA metrics depends on both the hand used to perform movements and the side of the body on which movements occur.
- Provided the first empirical account of *how* each of the common KA metrics varies across reaches in different directions, when users reach on either side of their body using either hand.
- Revealed that when users reach on either side of their body using either hand, the effects of movement direction on common KA metrics can be different for different individual users.
- Revealed that in most cases, individual differences in arm length did not account for the between-participant differences in these effects.

However, as described above (Sections 5.2 and 5.3), there is still much more work to be done. There are more KA metrics to evaluate, more movement tasks for which to evaluate them, and more task properties to which they may be sensitive. There are also looming questions regarding how the influence of these task properties on KA metrics may depend on individual differences in anthropometric characteristics or other factors. Looking forward, we would like to encourage future researchers to take up the challenge of addressing these needs, as we plan to do in our laboratory. Like this dissertation, any individual study or set of studies will only chip away at a small piece of these needs. However, with continued effort, this basic research can lay the empirical foundation for the broad practical use of kinematic analyses in the coming decades.

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7 APPENDICES

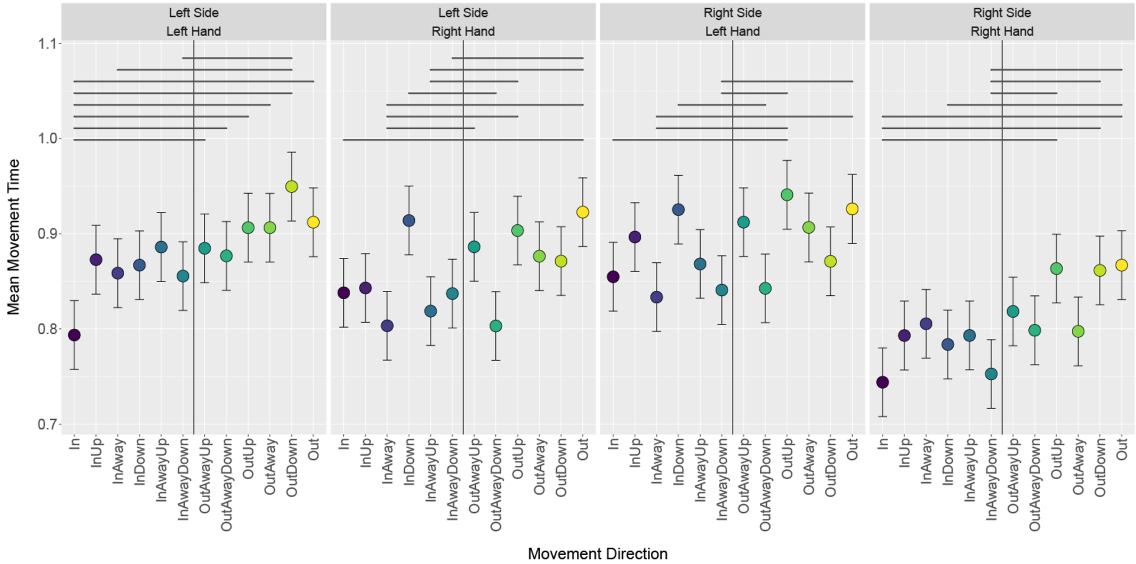
APPENDIX A: MEAN VALUES BY EXPERIMENTAL CONDITION FOR CHAPTER 2

Experimental Condition		Movement Time	Peak Velocity	PTPV	PTPSE	PSE Distance	SPARC
Left Side, Left Hand	Away	0.816	0.732	57.799	70.851	0.080	1.862
	Up	0.822	0.705	55.317	76.388	0.059	1.815
	Down	0.876	0.791	53.958	74.232	0.053	1.812
	Left	0.873	0.749	52.430	71.113	0.068	1.872
	Right	0.757	0.805	52.523	72.410	0.060	1.802
Left Side, Right Hand	Away	0.810	0.765	56.053	75.355	0.058	1.851
	Up	0.813	0.725	55.263	75.114	0.064	1.808
	Down	0.825	0.815	55.182	77.210	0.046	1.785
	Left	0.879	0.685	51.341	70.051	0.074	1.918
	Right	0.763	0.870	51.653	73.400	0.049	1.774
Right Side, Left Hand	Away	0.856	0.713	53.526	71.350	0.066	1.852
	Up	0.836	0.765	53.147	75.192	0.060	1.808
	Down	0.871	0.781	51.771	70.407	0.056	1.807
	Left	0.791	0.864	49.517	70.845	0.052	1.778
	Right	0.905	0.656	50.201	63.619	0.092	1.892
Right Side, Right Hand	Away	0.762	0.724	60.626	72.893	0.078	1.846
	Up	0.782	0.715	57.520	77.677	0.064	1.796
	Down	0.869	0.788	52.157	71.800	0.052	1.809
	Left	0.715	0.865	53.377	74.444	0.057	1.765
	Right	0.854	0.750	52.612	74.492	0.059	1.893

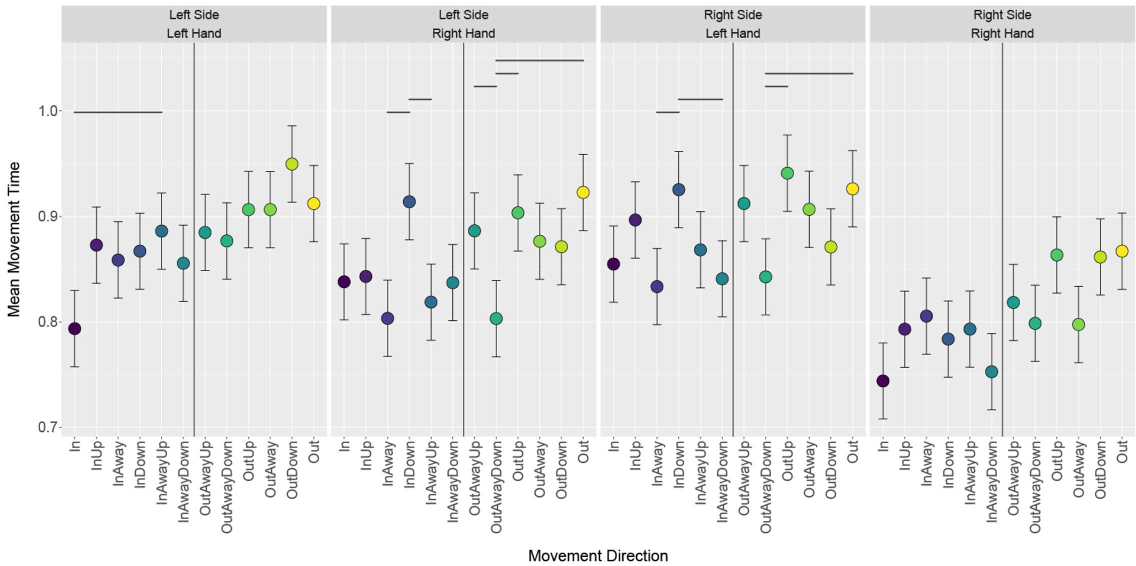
APPENDIX B: DOTPLOTS OF MEAN VALUES BY CONDITION FOR CHAPTER 3

Movement Time

A: Inward vs. Outward



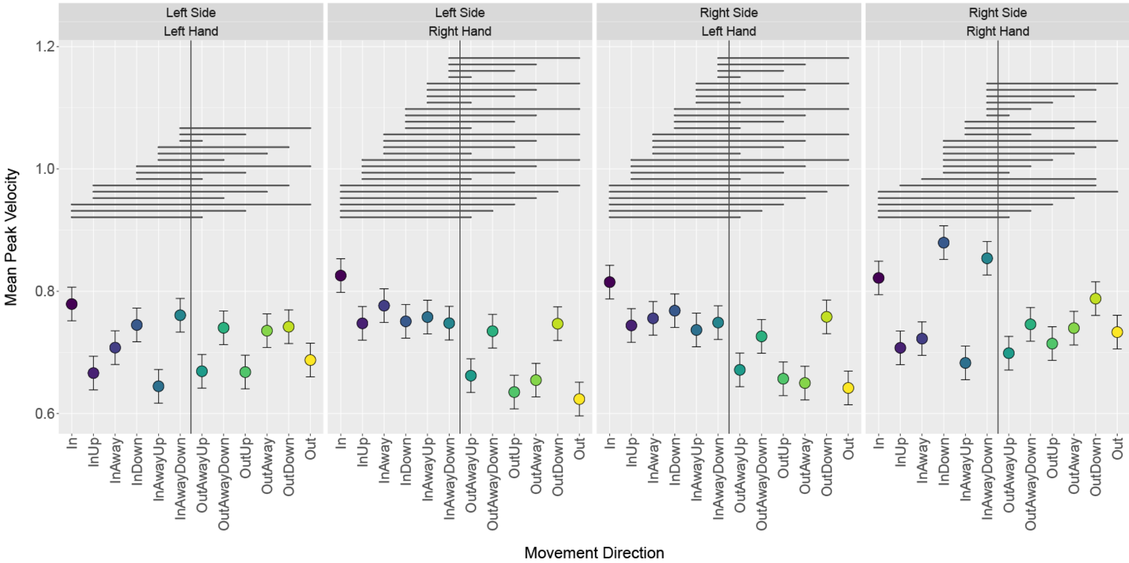
B: Inward vs. Inward & Outward vs. Outward



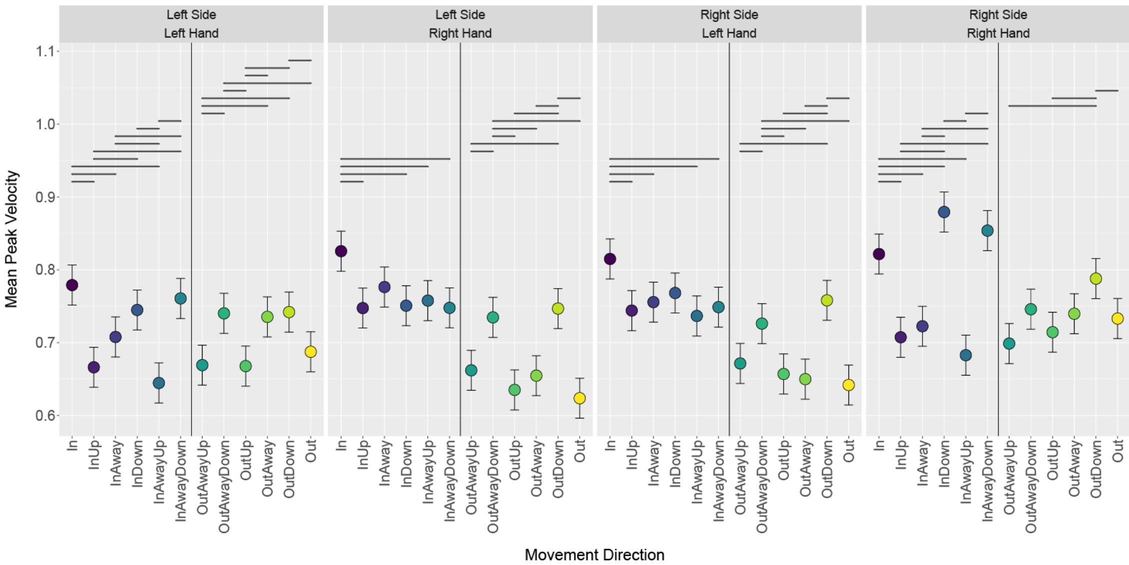
Mean *MT* values for reaches in each direction, for each combination of *hand* and *side*. Error bars reflect +/- 1 SE. The horizontal lines indicate significant differences (Tukey adjusted $p < .05$). Part (A) summarizes significant differences between inward and outward directions, and part (B) summarizes significant differences among reaches in the different inward directions and among reaches in the different outward directions.

Peak Velocity

A: Inward vs. Outward



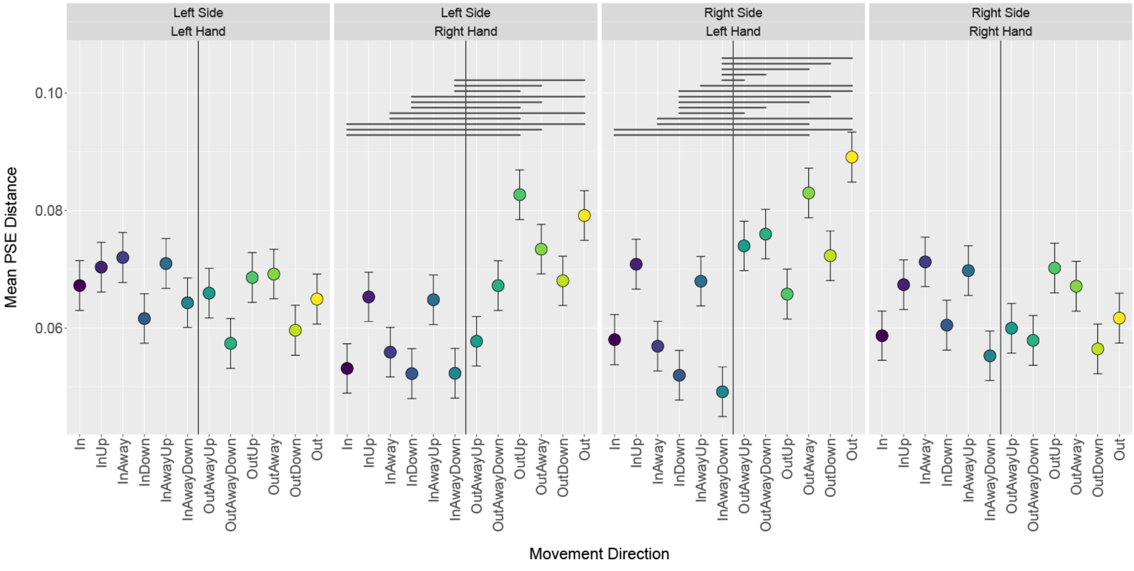
B: Inward vs. Inward & Outward vs. Outward



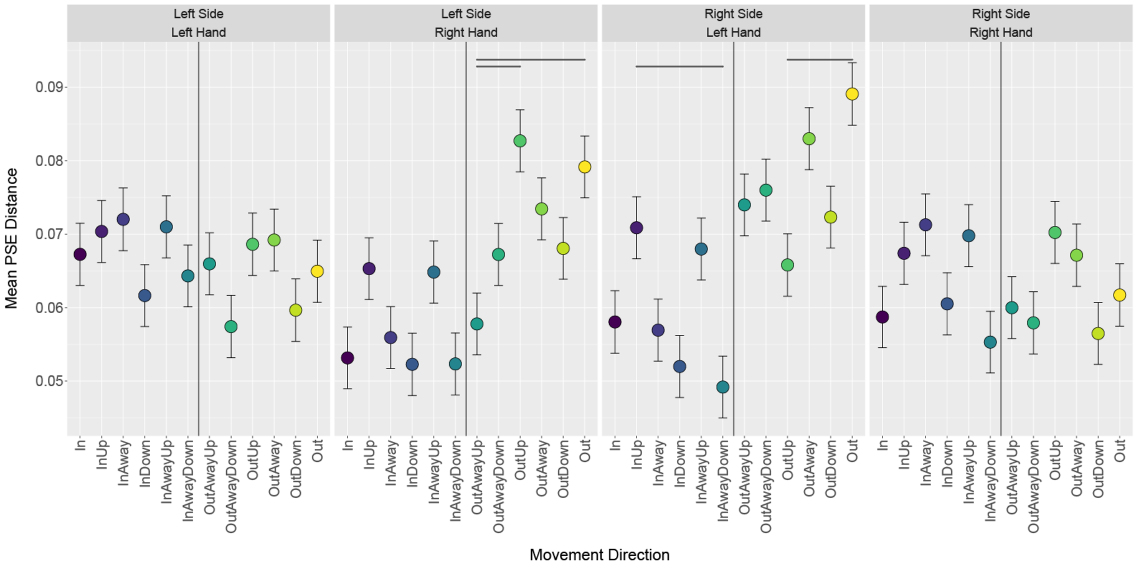
Mean v_{peak} values for reaches in each direction, for each combination of *hand* and *side*. Error bars reflect +/- 1 SE. The horizontal lines indicate significant differences between inward and outward reaches (Tukey adjusted $p < .05$). Part (A) summarizes significant differences between inward and outward directions, and part (B) summarizes significant differences among reaches in the different inward directions and among reaches in the different outward directions.

PSE Distance

A: Inward vs. Outward

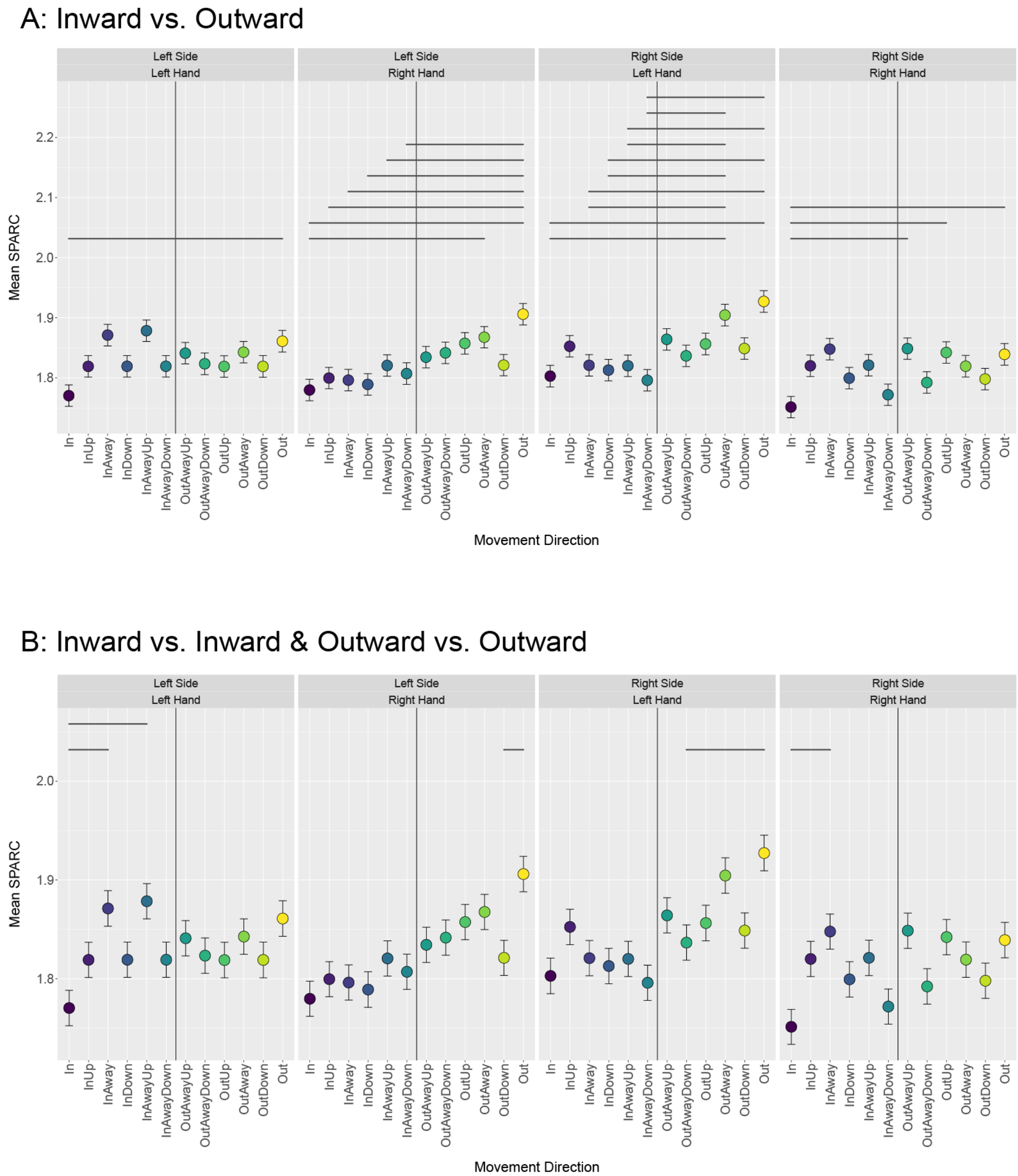


B: Inward vs. Inward & Outward vs. Outward



Mean d_{PSE} values for reaches in each direction, for each combination of *hand* and *side*. Error bars reflect +/- 1 SE. The horizontal lines indicate significant differences between inward and outward reaches (Tukey adjusted p < .05). Part (A) summarizes significant differences between inward and outward directions, and part (B) summarizes significant differences among reaches in the different inward directions and among reaches in the different outward directions. d_{PSE} is quantified using Unity units. The total distance from the starting position to the target was 0.20 units, so a d_{PSE} of 0.08 indicated that users ended their primary submovements with 40% of the total movement distance left to travel. The difference between a d_{PSE} of 0.05 and 0.08 corresponds to a difference of 15% of the total movement distance.

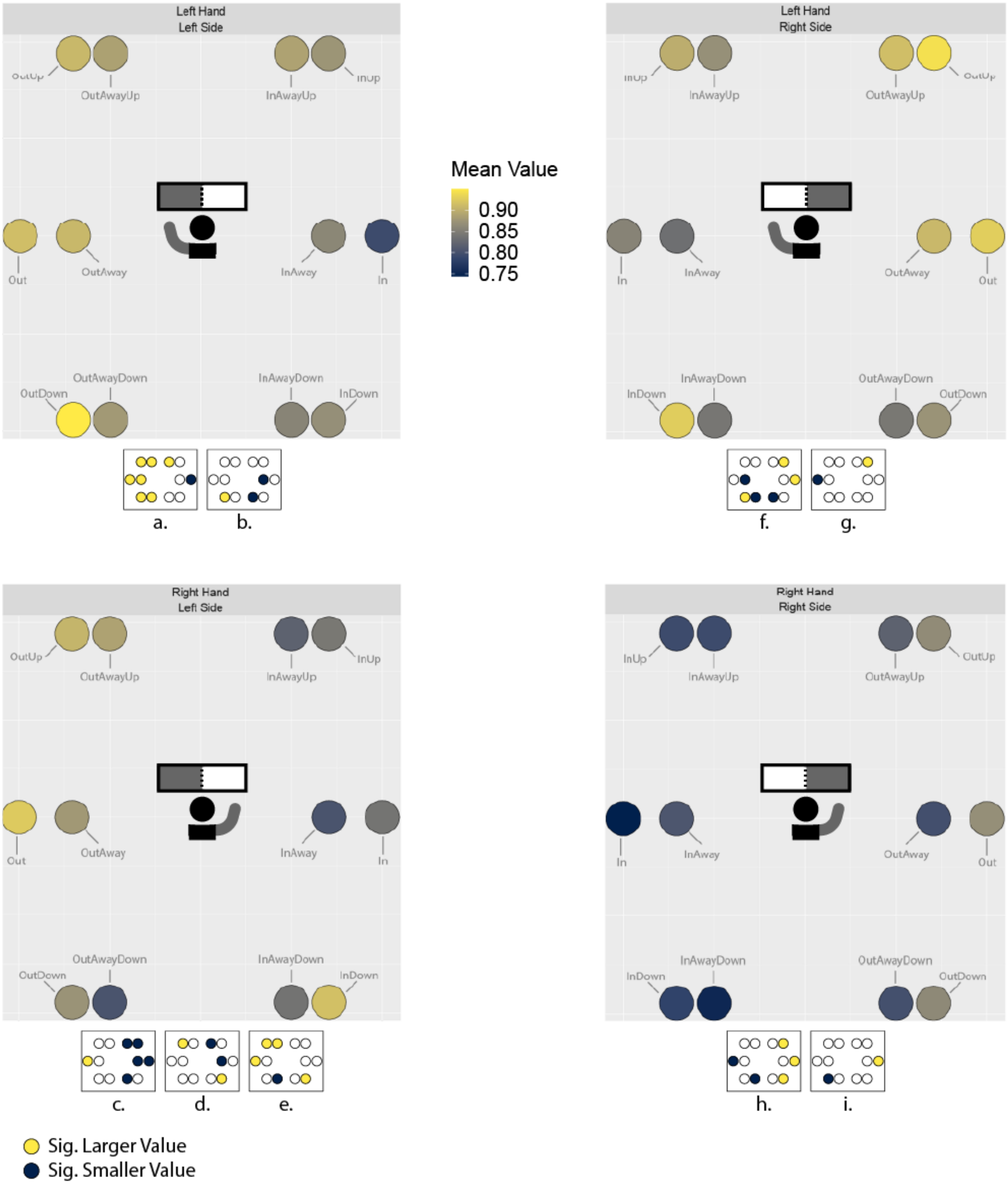
SPARC



Mean $SPARC$ values for reaches in each direction, for each combination of *hand* and *side*. Error bars reflect +/- 1 SE. The horizontal lines indicate significant differences between inward and outward reaches (Tukey adjusted $p < .05$). Part (A) summarizes significant differences between inward and outward directions, and part (B) summarizes significant differences among reaches in the different inward directions and among reaches in the different outward directions.

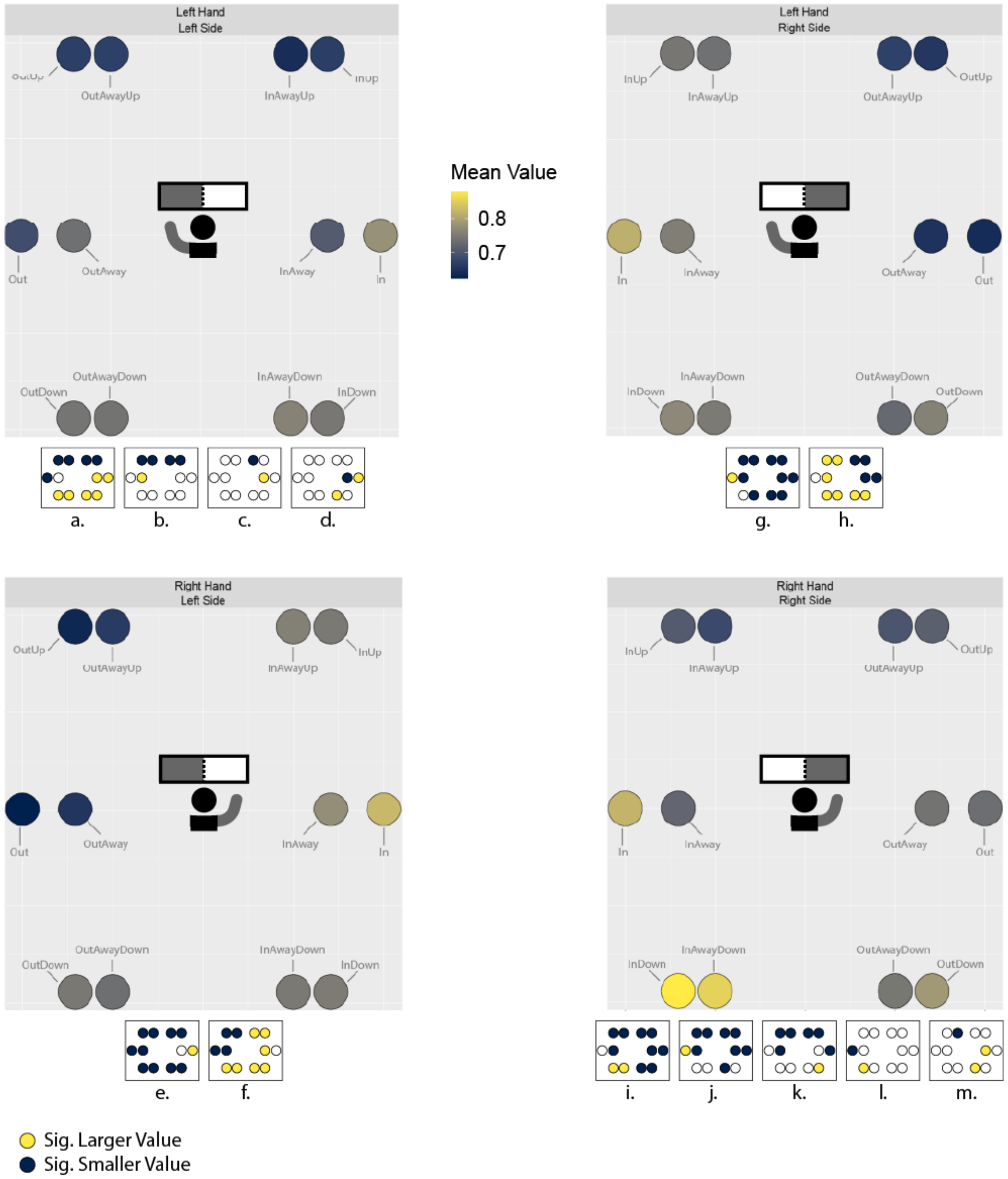
APPENDIX C: SPATIAL VIEW OF THE MEAN VALUES FOR EACH METRIC FOR CHAPTER 3

Movement Time



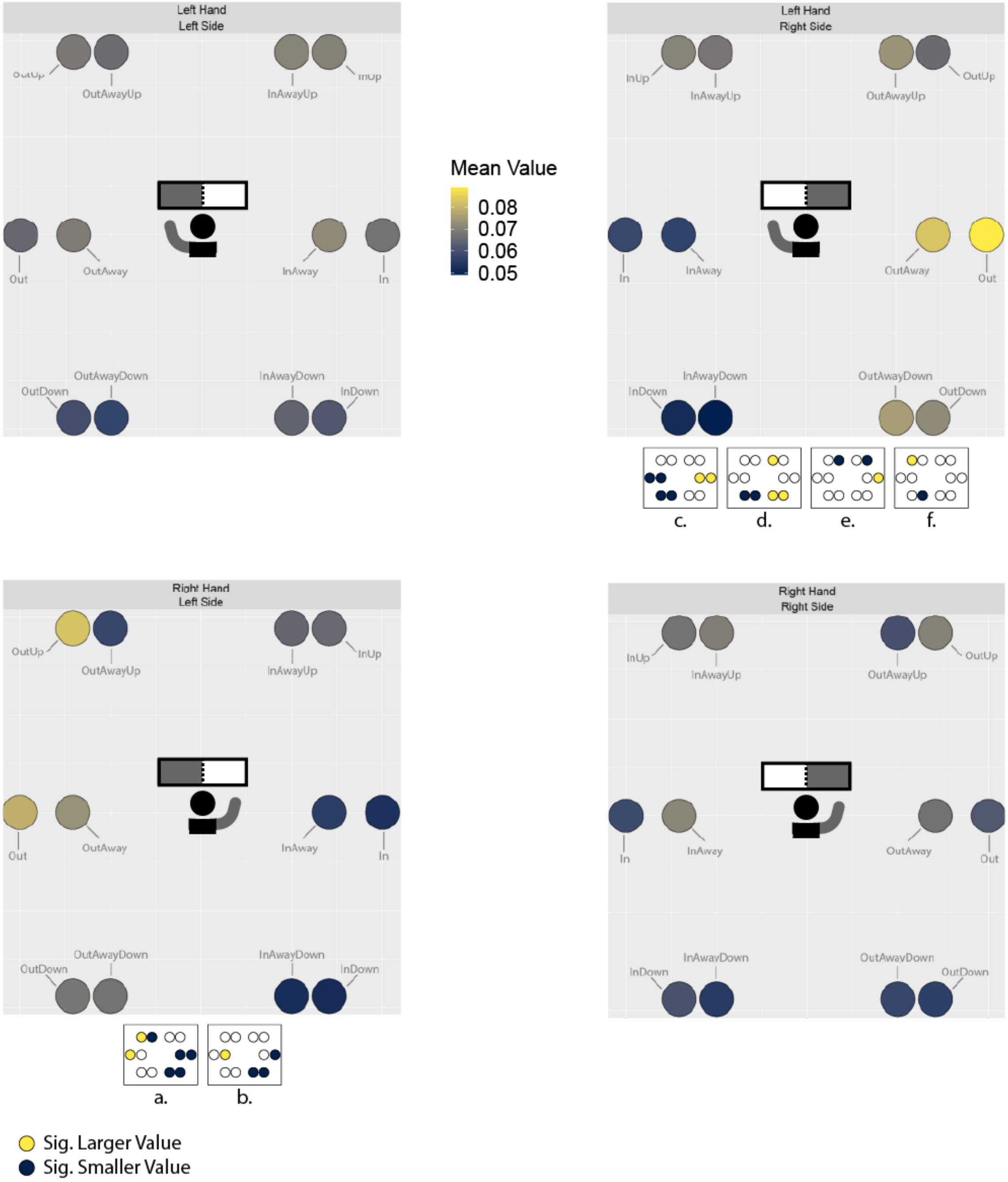
A spatial view of how MT changed as a function of movement direction for each combination of hand and side. The colors in each panel represent the mean MT value for each of the 12 movement directions, with lighter colors indicating larger MT and darker colors indicating smaller MT.

Peak Velocity



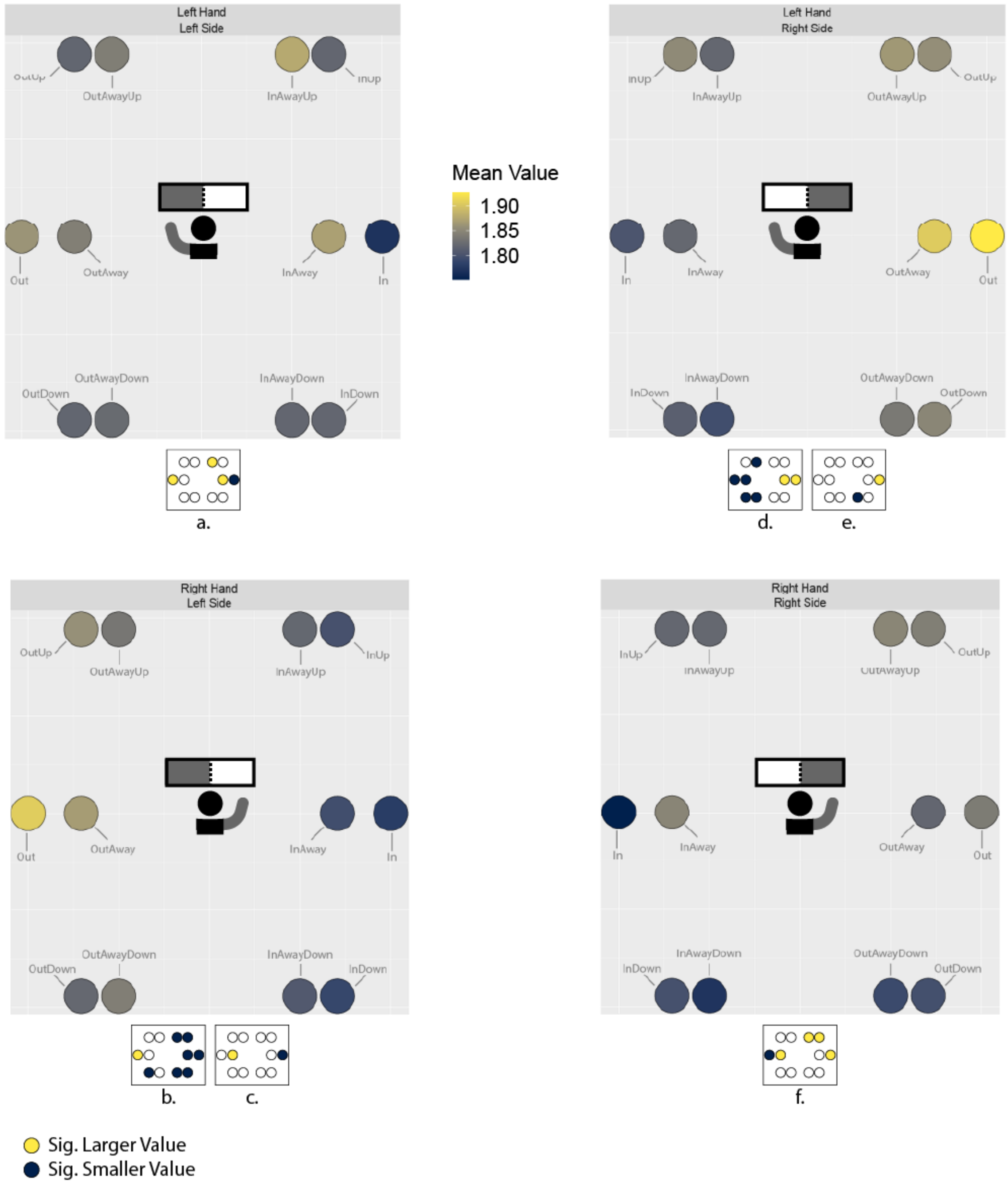
A spatial view of how v_{peak} changed as a function of movement direction for each combination of hand and side. The colors in each panel represent the mean v_{peak} value for each of the 12 movement directions, with lighter colors indicating larger v_{peak} and darker colors indicating smaller v_{peak}.

PSE Distance



A spatial view of how d_{PSE} changed as a function of movement direction for each combination of hand and side. The colors in each panel represent the mean d_{PSE} value for each of the 12 movement directions, with lighter colors indicating larger d_{PSE} and darker colors indicating smaller d_{PSE}.

SPARC



A spatial view of how $SPARC$ changed as a function of movement direction for each combination of hand and side. The colors each panel represent the mean $SPARC$ value for each of the 12 movement directions, with lighter colors indicating larger $SPARC$ and darker colors indicating smaller $SPARC$.

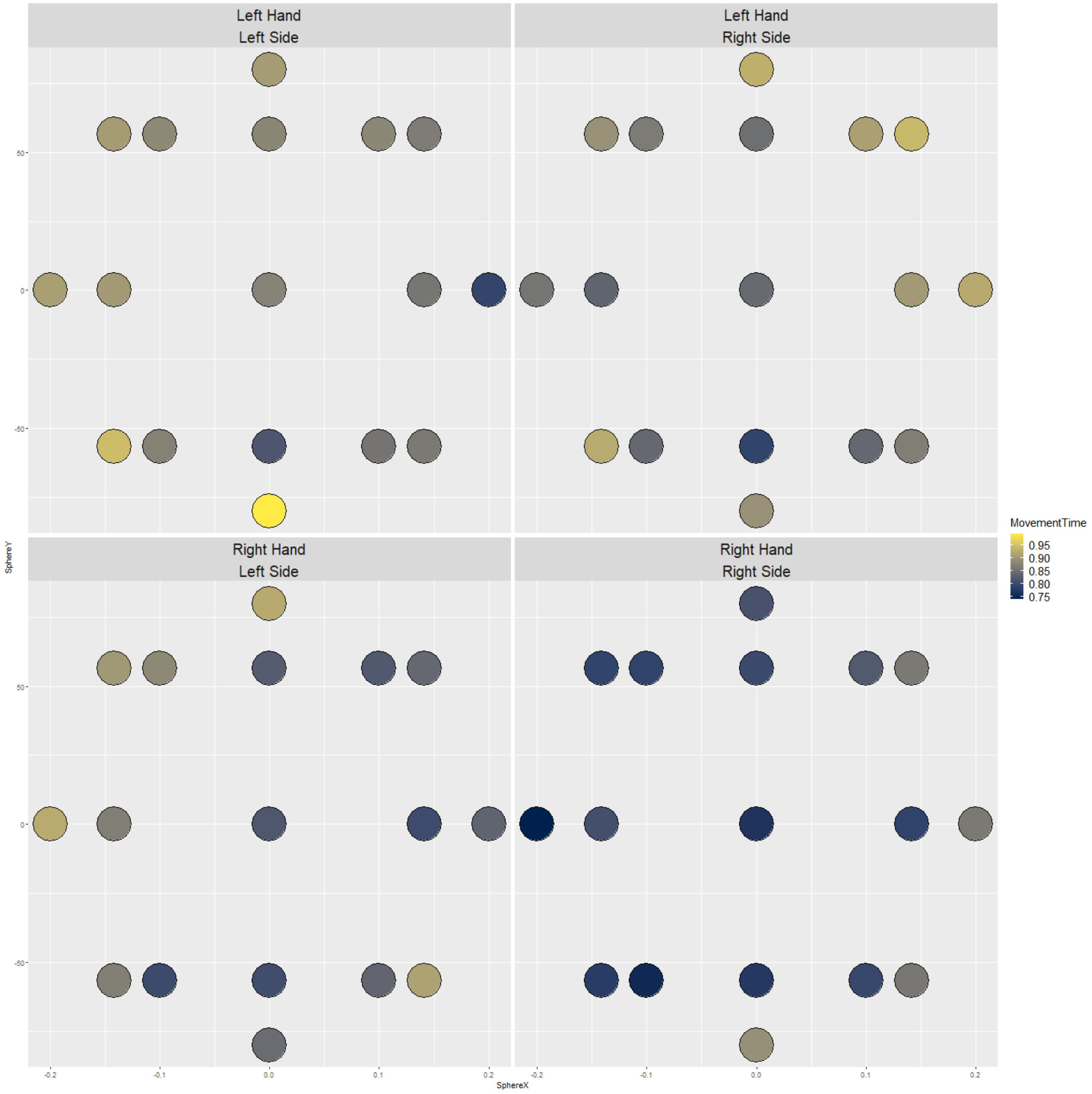
APPENDIX D: MEAN VALUES BY EXPERIMENTAL CONDITION FOR CHAPTER 3

	Location	Movement Time	Peak Velocity	PSE Distance	SPARC
Left Side, Left Hand	In	0.794	0.779	0.067	1.770
	InUp	0.873	0.666	0.070	1.819
	InAway	0.859	0.708	0.072	1.871
	InDown	0.867	0.745	0.062	1.819
	InAwayUp	0.886	0.645	0.071	1.878
	InAwayDown	0.856	0.761	0.064	1.819
	OutAwayUp	0.885	0.669	0.066	1.841
	OutAwayDown	0.877	0.740	0.057	1.823
	OutUp	0.906	0.668	0.069	1.819
	OutAway	0.906	0.735	0.069	1.843
	OutDown	0.950	0.742	0.060	1.819
	Out	0.912	0.687	0.065	1.861
Left Side, Right Hand	In	0.838	0.826	0.053	1.780
	InUp	0.843	0.747	0.065	1.800
	InAway	0.803	0.776	0.056	1.796
	InDown	0.914	0.751	0.052	1.789
	InAwayUp	0.819	0.758	0.065	1.821
	InAwayDown	0.837	0.748	0.052	1.807
	OutAwayUp	0.886	0.662	0.058	1.834
	OutAwayDown	0.803	0.735	0.067	1.842
	OutUp	0.903	0.635	0.083	1.857
	OutAway	0.876	0.655	0.073	1.868
	OutDown	0.871	0.747	0.068	1.821

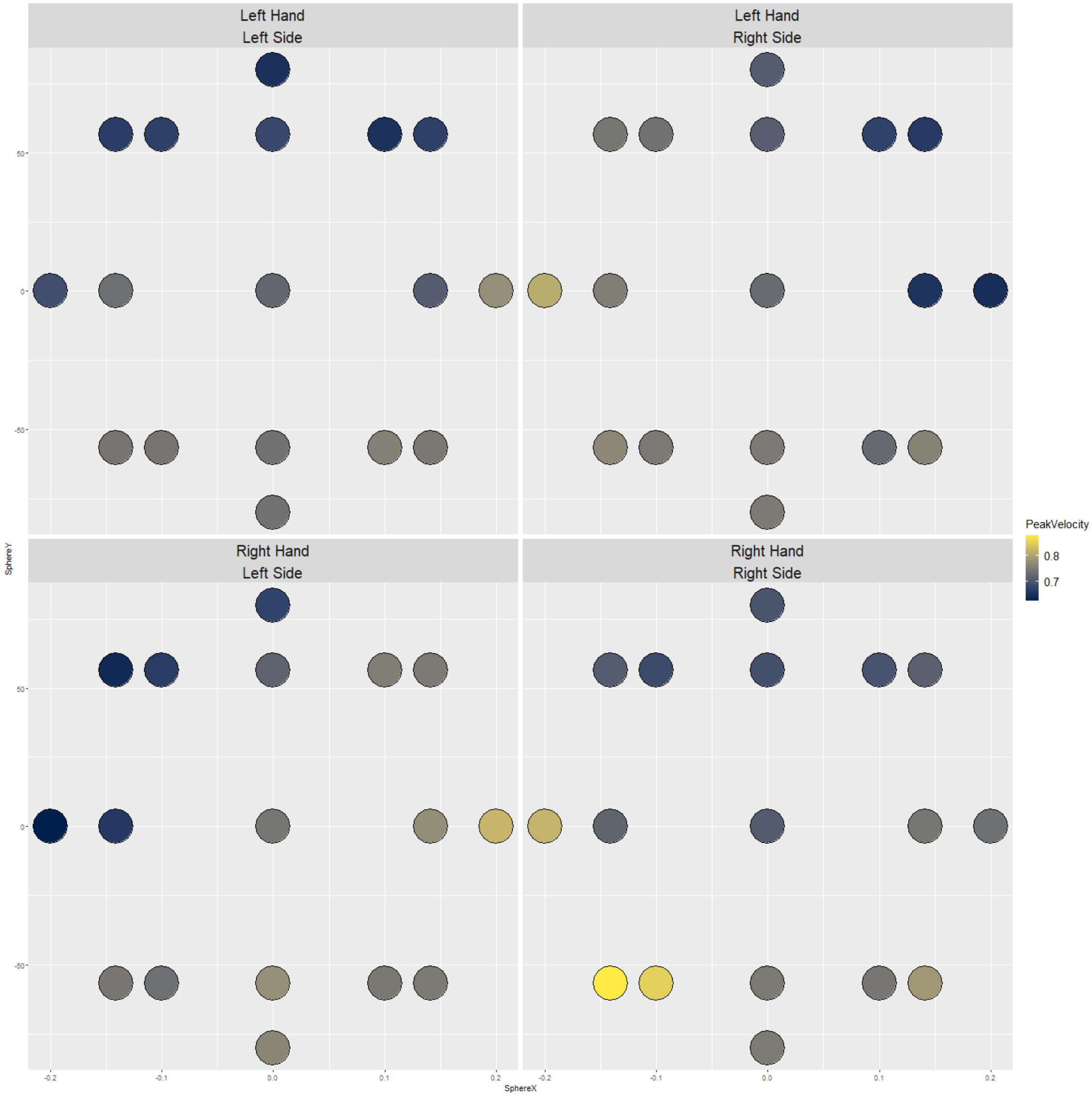
	Location	Movement Time	Peak Velocity	PSE Distance	SPARC
	Out	0.923	0.624	0.079	1.906
Right Side, Left Hand	In	0.855	0.815	0.058	1.803
	InUp	0.897	0.744	0.071	1.852
	InAway	0.833	0.756	0.057	1.821
	InDown	0.925	0.768	0.052	1.813
	InAwayUp	0.868	0.737	0.068	1.820
	InAwayDown	0.841	0.749	0.049	1.796
	OutAwayUp	0.912	0.671	0.074	1.864
	OutAwayDown	0.843	0.726	0.076	1.837
	OutUp	0.941	0.657	0.066	1.856
	OutAway	0.907	0.650	0.083	1.904
	OutDown	0.871	0.758	0.072	1.849
	Out	0.926	0.642	0.089	1.927
Right Side, Right Hand	In	0.744	0.822	0.059	1.751
	InUp	0.793	0.707	0.067	1.820
	InAway	0.806	0.722	0.071	1.848
	InDown	0.784	0.879	0.061	1.799
	InAwayUp	0.793	0.683	0.070	1.821
	InAwayDown	0.753	0.854	0.055	1.772
	OutAwayUp	0.818	0.699	0.060	1.849
	OutAwayDown	0.799	0.746	0.058	1.792
	OutUp	0.863	0.714	0.070	1.842
	OutAway	0.798	0.740	0.067	1.819
	OutDown	0.862	0.788	0.056	1.798
	Out	0.867	0.733	0.062	1.839

APPENDIX E: SPATIAL VIEW OF THE MEAN VALUES FOR ALL METRICS FROM CHAPTER 3, INCLUDING DIRECTIONS NOT EXAMINED IN THE PRESENT ANALYSIS

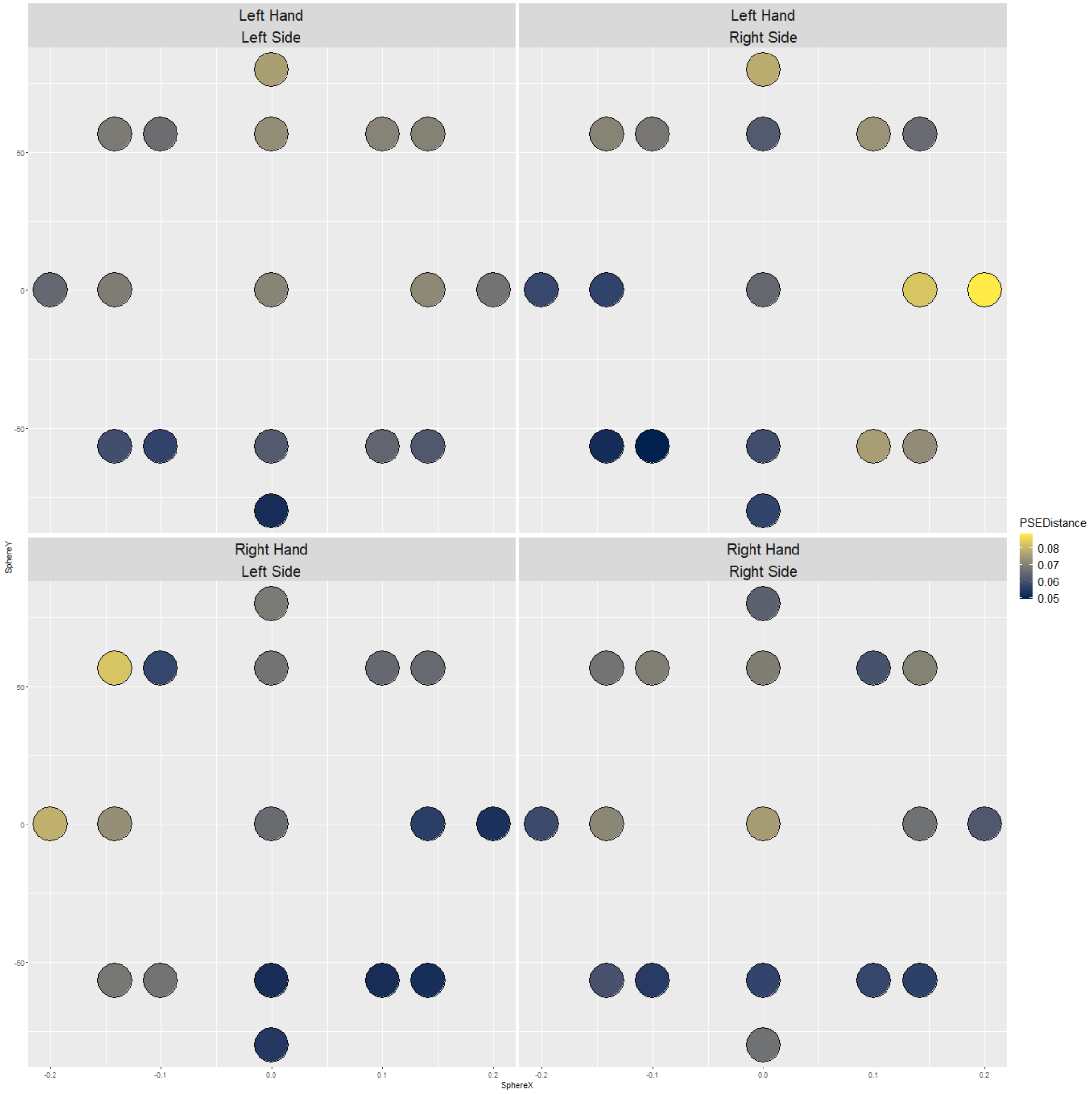
Movement Time



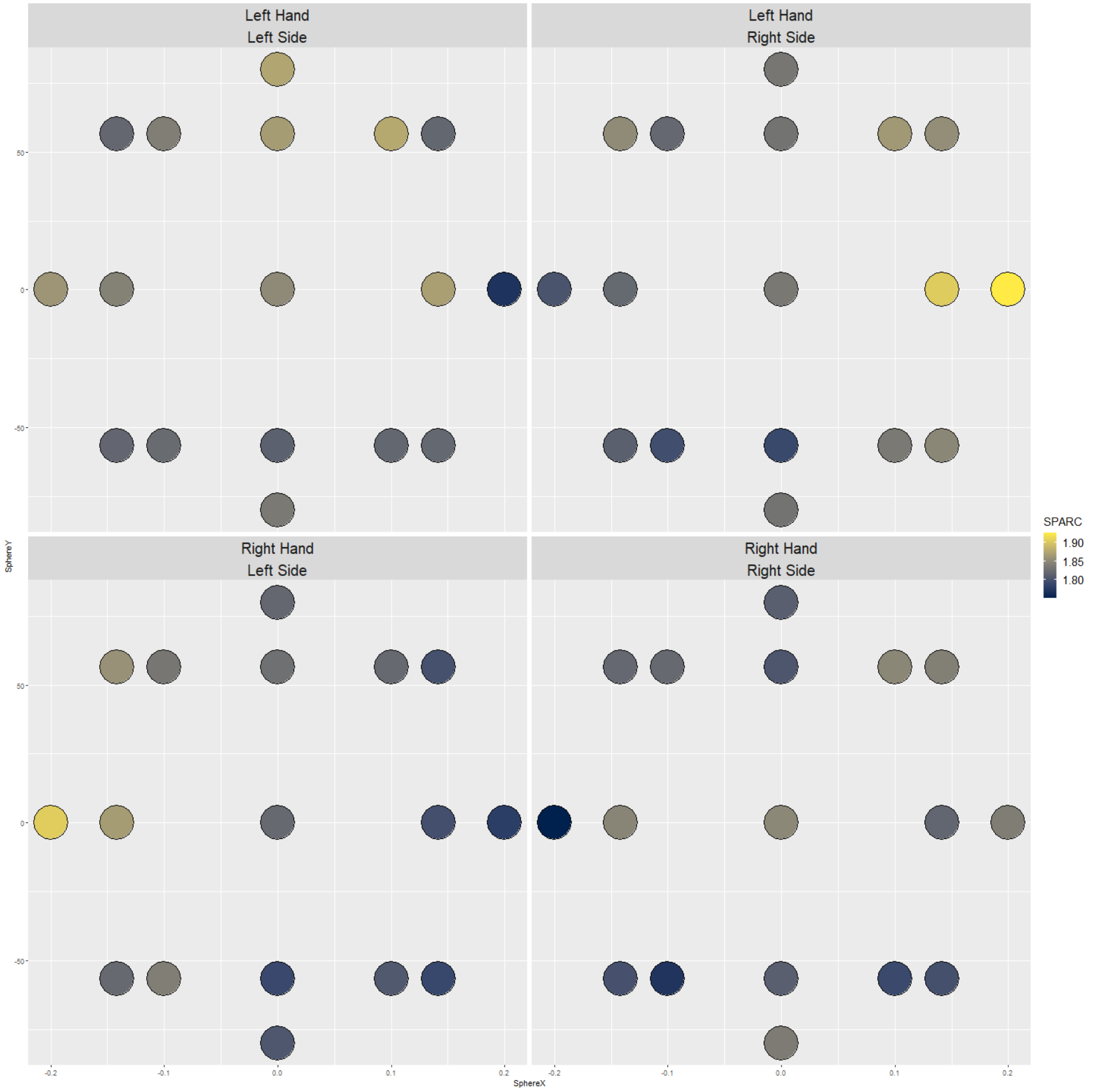
Peak Velocity



Primary Submovement Endpoint Distance



Spectral Arc Length



APPENDIX F: SLOPES AND BETWEEN-PARTICIPANT STANDARD DEVIATIONS FOR CHAPTER 4

Differences Between Reaches *In* and *Out*

		In – Out Slope	SD
Movement Time	LS_LH	-0.0625	0.0316
	LS_RH	-0.0462	0.0797
	RS_LH	-0.0557	0.0493
	RS_RH	-0.0584	0.0561
Peak Velocity	LS_LH	0.0544	0.0809
	LS_RH	0.1687	0.0969
	RS_LH	0.1471	0.0841
	RS_RH	0.0748	0.0746
SPARC	LS_LH	-0.0672	0.0648
	LS_RH	-0.0657	0.0324
	RS_LH	-0.0891	0.0556
	RS_RH	-0.0378	0.1002
PSE Distance	LS_LH	0.0072	0.0135
	LS_RH	-0.0244	0.0133
	RS_LH	-0.0322	0.0158
	RS_RH	-0.0001	0.0030

Differences Between Reaches *Up* and *Down*

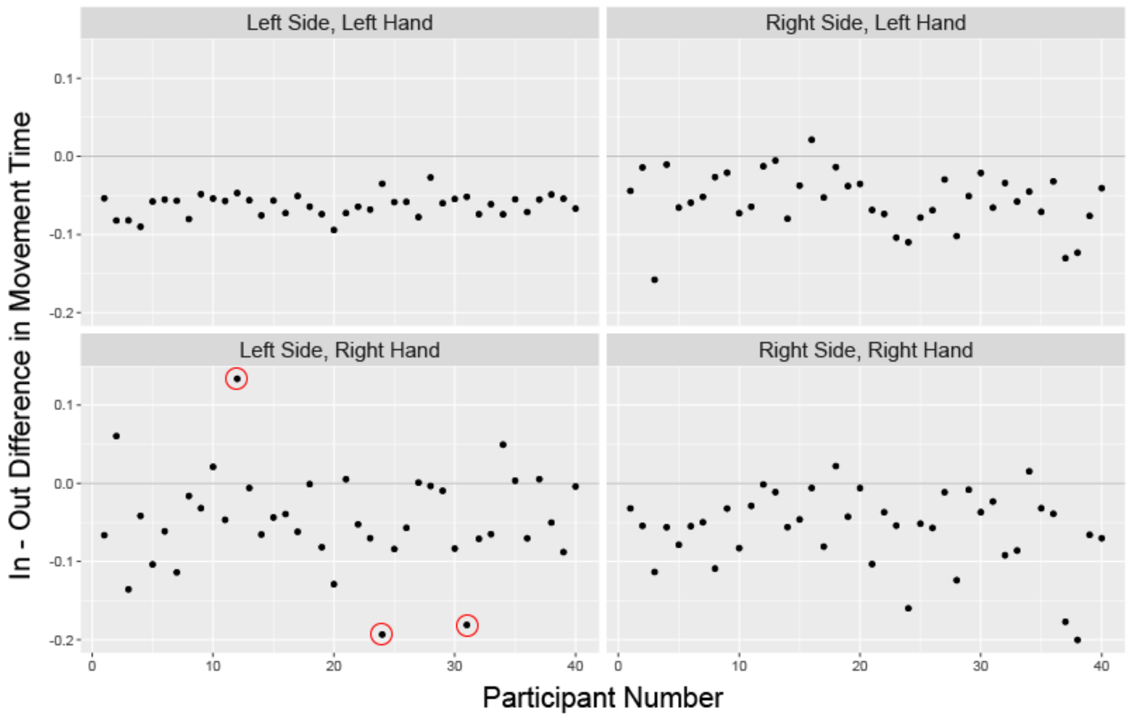
		Up – Down Slope	SD
Peak Velocity	LS_LH	-0.0852	0.0774
	LS_RH	-0.0991	0.0924
	RS_LH	-0.0383	0.0874
	RS_RH	-0.0839	0.0762

Appendix G: Sensitivity Analysis for Chapter 4, Examining If/How Results Changed When Models Were Re-Fitted Without High-Influence Observations

For a few of the effects we examined in Chapter 4, influence diagnostics and empirical Bayes (EB) estimates of participant-level slopes suggested that a few participants may have exhibited an outsized influence on the model parameters. For each of these cases, we re-fitted the model without the data from the influential participant and examined if this meaningfully influenced our results. This enabled us to ensure that our results were not entirely caused by a small number of unusual but highly influential observations. Here, we report the results of this sensitivity analysis in detail.

Movement Time

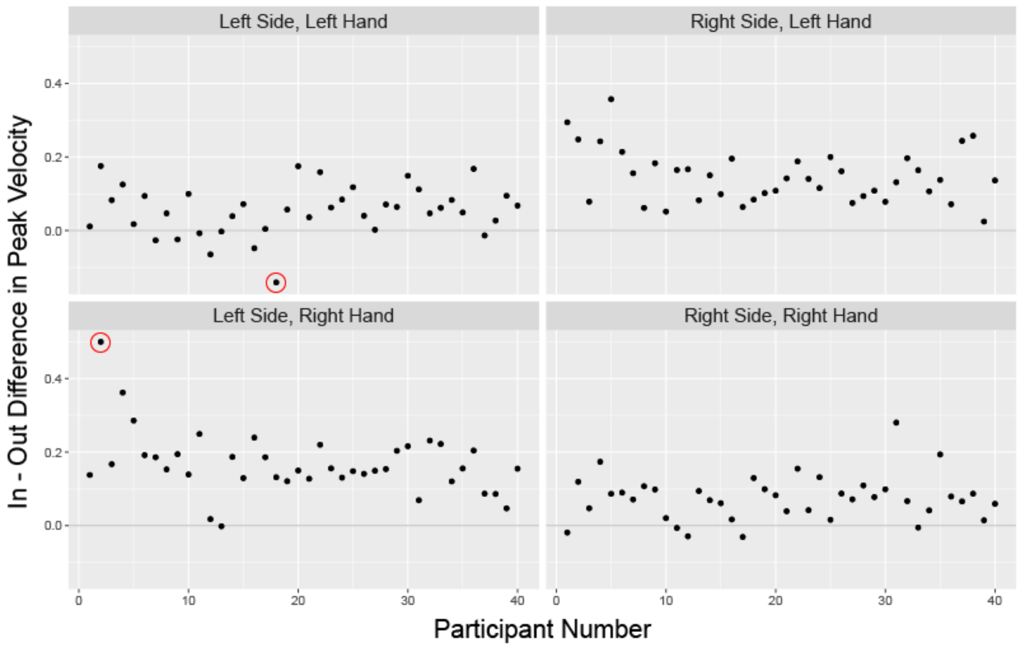
First, for reaches performed on the left side using the right hand, EB estimates of the difference in MT between inward and outward reaches for each participant suggested that one participant (P12) exhibited a particularly large positive difference (i.e., MT much larger for inward than for outward), while two others (P24 and P31) exhibited a particularly large negative difference (i.e., MT much smaller for inward than for outward). Refitting the model without these participants did not meaningfully impact the results. There was still a significant fixed effect for *direction*, and the *direction* x *arm length* cross-level interaction was still not significant.



Peak Velocity

For reaches on the left side using the left hand, analysis of influence metrics and participant-level slope estimates revealed that one participant (P18) exhibited a particularly large negative difference in v_{peak} between inward and outward reaches (i.e., smaller v_{peak} when reaching inward than when reaching outward). When the model was refitted without this participant, there was still a significant fixed effect for *direction*. However, without this participant, the *direction* x *arm length* interaction effect no longer reached significance (*p* = .34). This suggests that this effect was largely driven by this one influential participant.

For reaches on the left side using the right hand, influence metrics also revealed that one participant (P2) exhibited particularly a particularly large positive difference in v_{peak} between inward and outward reaches (i.e., larger v_{peak} when reaching inward than when reaching outward. Refitting the model without this participant did not substantively influence the likelihood ratio test results. There was still a significant fixed effect for *direction* and the cross-level interaction still did not reach significance.



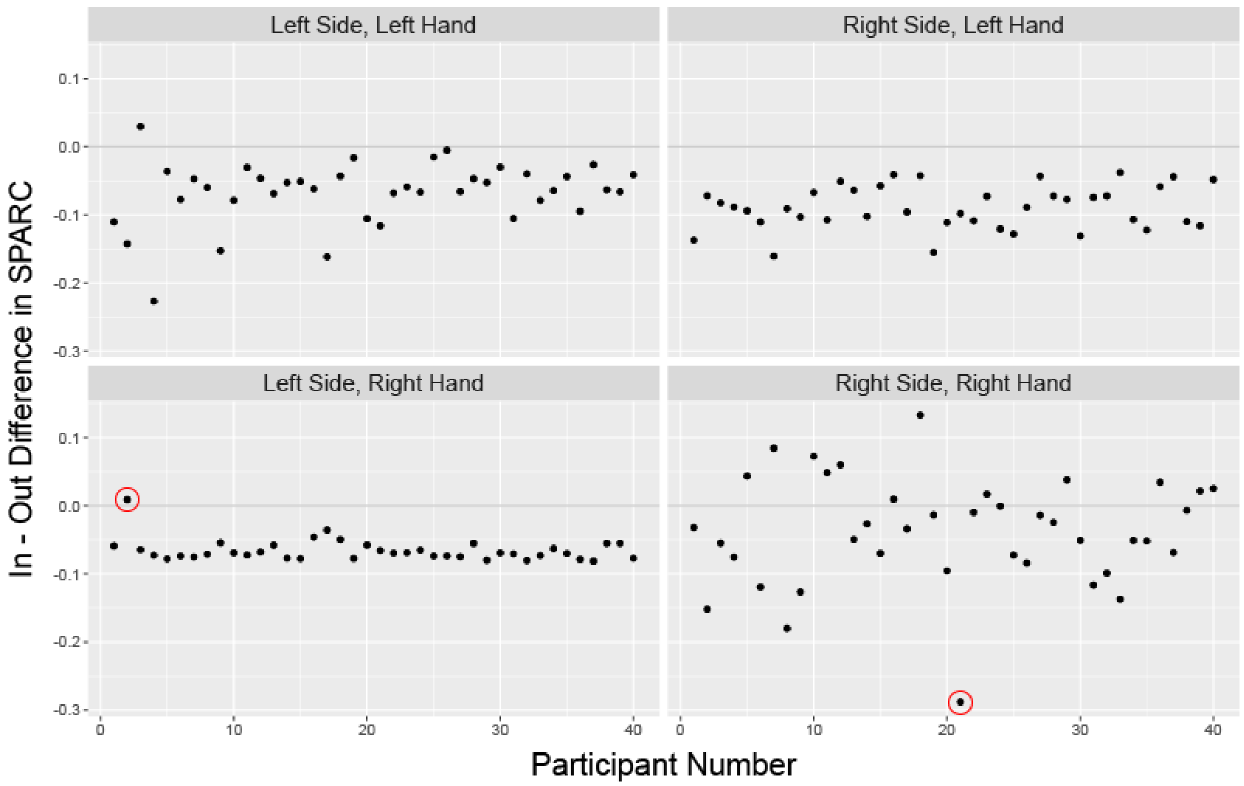
Primary Submovement Distance

Analysis of influence metrics and residual diagnostics did not reveal any potential high-influence observations for d_{PSE}.

Spectral Arc Length

Finally, analysis of influence metrics and EB estimates of participant-level slopes indicated that when users reached on the right side of their body using their right hand, one participant (P21) exhibited an unusually large negative difference in $SPARC$ between inward and outward reaches (i.e., much smaller $SPARC$ for inward reaches than for outward reaches). Refitting the model without this participant yielded the same likelihood ratio test results. The fixed effect for *direction* still fell short of statistical significance (p = .28), and the slope estimate for this effect indicated that on average users tended to exhibit slightly smaller $SPARC$ when reaching inward than when reaching outward.

Also, when users reached on the left side of their body using their right hand, one participant (P2) exhibited a particularly large slope value. Refitting the model without this influential participant yielded the same likelihood ratio test results. There was still a significant fixed effect for *direction* and the *direction* x *arm length* interaction still fell short of statistical significance.


Left Side, Left Hand
Right Side, Left Hand
Left Side, Right Hand
Right Side, Right Hand
In - Out Difference in SPARC
Participant Number
0.1
0.0
-0.1
-0.2
-0.3
0
10
20
30
40