Tailor Twist: Assessing Rotational Mid-Air Interactions for Augmented Reality

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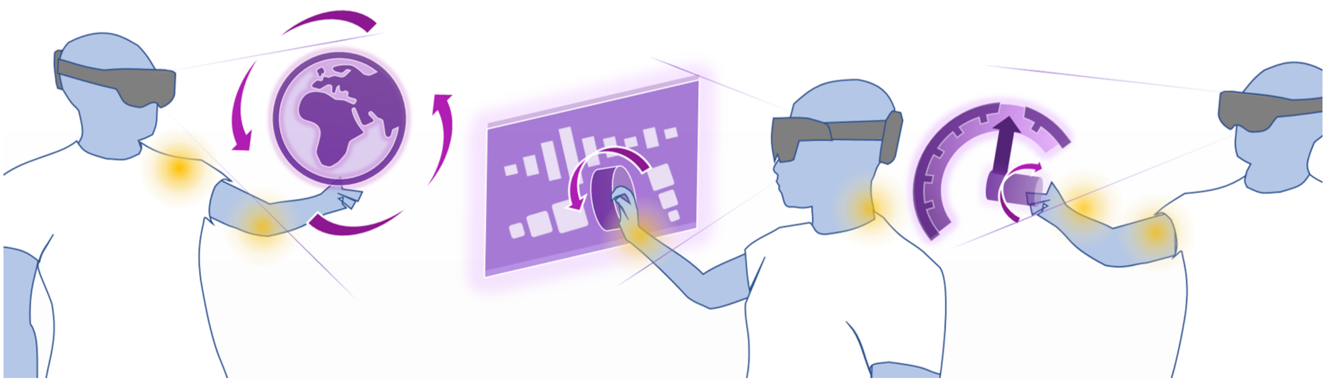

Figure 1: We investigate the ergonomics of rotational mid-air interaction for Augmented Reality (AR) environments, applicable for different use cases, such as virtual object manipulation or controlling augmented user interfaces. Blue depicts the user, purple augmented virtual contents, and yellow ergonomic-critical body parts during mid-air gesturing that can result in strain, muscle fatigue, and discomfort.

ABSTRACT

Mid-air gestures, widely used in today's Augmented Reality (AR) applications, are prone to the "gorilla arm" effect, leading to discomfort with prolonged interactions. While prior work has proposed metrics to quantify this effect and means to improve comfort and ergonomics, these works usually only consider simplistic, one-dimensional AR interactions, like reaching for a point or pushing a button. However, interacting with AR environments also involves far more complex tasks, such as rotational knobs, potentially impacting ergonomics. This paper advances the understanding of the ergonomics of rotational mid-air interactions in AR. For this, we contribute the results of a controlled experiment exposing the participants to a rotational task in the interaction space defined by their arms' reach. Based on the results, we discuss how novel future mid-air gesture modalities benefit from our findings concerning ergonomic-aware rotational interaction.

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CCS CONCEPTS

• **Human-centered computing** → Gestural input.

KEYWORDS

Augmented Reality, Mid-Air Gesture, Rotational Interaction

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1 INTRODUCTION

Mid-air gestures are arguably the central interaction techniques of today's Augmented Reality (AR) Head-Mounted Displays (HMDs), allowing users to directly manipulate virtual interface elements within their arm's reach. However, while this type of input enables fast and easily adaptable interaction, it imposes strain and fatigue [24, 28] on the user's shoulder and arms, ultimately leading to discomfort when used for a prolonged time. To facilitate ergonomic mid-air interactions, the design must consider the users' sense of comfort, influenced by for example, physical constraints, muscle fatigue, and exhaustion [2, 17]. This, however, requires a thorough understanding of the factors influencing the ergonomics of a mid-air interaction, such as position, interaction time, and task.

Prior work contributed metrics to assess and model the strain for arm movements [5, 24, 46] of such mid-air interactions. However, their models only account for arm movements on the way to specific locations and, thus, *translation* of the hand. Yet, our interaction with AR interfaces is typically more complex: Besides using translation for pushing buttons, we grab elements, pinch to zoom, or rotate knobs. In particular, such rotational manipulations are among the most demanding since they require very complex hand and finger movements, including a complete arm and partial thorax motion [68]. Even though today's mid-air gestures make heavy use of such rotational interactions, see Figure 1, we still miss an in-depth understanding of their impact on the ergonomics of the interaction.

In this paper, we systematically investigate the effects of mid-air rotation interaction in AR on discomfort, accuracy, and user behavior. We conducted an experiment with 19 participants that had to rotate an AR knobs at equidistributed locations around the body for different levels of proximity while seated and standing. As part of our results, we identified that the stance, as well as the rotation axis, does have an additional impact on the accuracy, comfort, and interaction count than just considering the task's location. Tasks should be presented close to the user's body, especially when seated, and rotated around an upwards rotation axis.

To summarize, the contributions of this paper are:

(1) A systematic evaluation (N=19) of perceived ergonomics of mid-air rotations in AR varying pose, task alignment, and position.
(2) A proposed design space for ergonomic-aware rotational mid-air interaction based on the study results.
(3) A set of recommendations for future ergonomic-aware AR interfaces.

2 RELATED WORK

In this section, we summarize previous research concerning the interaction with AR interfaces. Then, we characterize the challenges of creating ergonomic AR interfaces, focusing on mid-air gestures in particular. Finally, we present research focusing on improving several aspects of mid-air interaction.

2.1 Overview of Existing AR Interaction Modalities

Research examined several AR interaction modalities. They range from specially designed Mixed Reality (MR) controllers for AR input [55, 75] but also to everyday objects used as a controller. Al-Sada et al. [1] presented embedded inputs from smart wearables to interact with augmented worlds. Additional research explored AR interaction using smartphones [11, 34, 35, 47, 67], tablets [25, 40], or smartwatches [32, 51, 56, 76]. Moreover, research showed techniques to include everyday available tangibles as AR input modality [15], such as pens [16, 55]. While these approaches utilize relatively common objects as input devices, researcher also created plenty of custom-built AR controllers [69, 70]. This allows for improved ergonomic-awareness, like lowered hands, close-to-body interaction, and angled [29] hand posture. However, using objects as an input device requires them to be carried around, even when not interacting, which could be cumbersome in on-the-go scenarios. Moreover, these devices occupy a hand during an interaction.

One hands-free approach for AR interaction is by using gestures. A possible way for gesture input is by using the body as input for gestures. Previous research utilized the whole body [20] or just parts of it, like forearm [21], palm [50], abdomen [71] or face [65, 77]. Additionally, eye gaze has been utilized as input [3, 41, 52, 59]. Another possibility to interact on or around the body are the mid-air gestures [10, 44, 62, 72]. Using hand movement and postures in the air allows for direct manipulation of the AR within arm's reach [48]. A great advantage of mid-air gestures, is their versatility, for example, Jahani et al. [27] analysed 900 hand gestures just for in-vehicle interfaces. Mid-air gestures can be adapted to nearly every surrounding and use case. This feature gave them a place as one of the default input methods in most AR HMDs nowadays. Gaining comprehensive insights of the ergonomic-awareness of mid-air gestures could benefit the further exploration of AR interfaces, as shortcomings and drawbacks can be addressed by the design of User Interfaces or compensated by multimodal approaches with other input modalities mentioned earlier.

2.2 Ergonomics of Mid-Air Gestures

Mid-air gestures are one of the most popular input modalities for AR. However, due to its non-tangible nature, such mid-air gestures often result in arm fatigue if the interfaces are not properly fitting the user's ergonomics. Research describes this effect as "gorilla arm" [24, 28] which occurs when users are forced to hold their arms for a prolonged time in front of their body without support.

To quantify and potentially countermeasure the "gorilla arm" effect [24, 28], past research came up with multiple metrics to measure the strain of mid-air gestures. One is the Consumed Endurance [23, 24]. This metric is being deduced from the biomechanical structure of the upper arm to characterize the "gorilla arm" effect [24, 28]. Advantages of the Consumed Endurance [23, 24] is, that it can be assessed non-invasively and non-obtrusively using, for example, the Microsoft Kinect [23], and therefore being conducted in real-time and objectively, compared to questionnaires.

Another approach, which assesses the loads on the musculoskeletal system based on the posture of the users, is RULA [46]. RULA classifies postures of different limb parts in groups to finally score the load and strain. This is an easy-to-apply approach and can also be applied without heavy computation. There are even tools for automatic detection and quantification based on video feeds for example [45, 57].

Similar approaches use biomechanically modeling and simulation to measure perceived arm fatigue using a visual approach [28] and Deep Reinforcement Learning [12]. Bachynsky et al. [5] further explored the muscle activation of interaction in the reachable space. Based on these findings, we can identify regions inside this space with low muscle activation and strain on the biomechanics of the upper arm. This space is favorable for user interaction due to its low impact on the human body.

The presented works build a great foundation and first impression of interaction in mid-air. However, they do only consider the physiology of arm movement, with no specific focus on AR interaction. Therefore, this work focuses on the use case of AR interaction.

2.3 Improving Ergonomics of Mid-Air Interaction

To reduce negative effects due to arm fatigue and high strain, research suggests to keep gestures relatively close to the body and in the lower area of the reachable space [5, 24]. To help designers with keeping their user interfaces and interactions in these defined areas, Belo et al. [18] developed XRgonomics. This toolkit supports developers while designing AR user interfaces by displaying comfortable spaces around the user and automatically moving elements outside these areas to more comfortable regions.

While XRgonomics shifts the augmented world around to maintain a more comfortable posture, other research maintains the task's original position. However, it allows the hand to be positioned in a more comfortable way. For example, Feuchtner and Müller [19] introduced hand retargeting in their work. When interacting with digital content for too long in too high positions, the system gradually increases the offset between the real hand and a digital representation of it to guide the user's real hand into a more comfortable position. This way, a more comfortable posture can be achieved, while interacting with digital bits at their original location.

Similar, ERG-O [49] presents an approach to move far away tasks close to the body, so the user can manipulate virtual objects in comfortable spaces. The same principle can even be applied to Virtual Reality (VR) controllers [73] or just hands [78] and their gestures [43].

2.4 Summary

While we see many opportunities to interact in AR, mid-air gestures remained a state-of-the-art input modality. At the same time, previous work informed us about ergonomic postures and how to comfortably reach certain points in the arm's reachable space. However, past research has not explored the impact of mid-air rotation gestures on the user's Comfort. As current metrics to quantify comfort, such as RULA [46] and the Consumed Endurance [23, 24], do only consider parts of the mid-air gestures, i.e., reaching for the location. In contrast, we explore the rotation gesture itself. To fully understand AR mid-air gestures, we need to explore translation, rotation, and scale object translation separately. Exploring these mid-air rotational manipulation is particularly interesting because of it requiring very complex movements of the hand and necessitates the entire arm and parts of the thorax to perform it [68] compared to translation for example, while still being a very important and common interaction.

3 METHODOLOGY

We conducted a controlled experiment to investigate the performance of rotating with mid-air gestures at various spatial locations and axis, either standing or sitting. We focus on rotation because it is a common manipulation practice, most well-known from physical interfaces, and has the potential to further enhance the expressiveness of AR interaction.

We define the following research questions:

RQ1 How do different rotation axis influence the accuracy, number of interactions, and comfort of rotational mid-air interactions?

RQ2 How does the stance and freedom of movement influence the accuracy, number of interactions, and comfort of rotational mid-air interactions?

RQ3 How does the location of the rotational AR interface influence the accuracy, number of interactions, and comfort?

3.1 Rotation Task

Based on the interaction concept of Hürst [26] and Bai et al. [6], we designed an AR rotation task using mid-air gestures. These gestures exploit finger pinching to express the willingness to interact with the task and to trigger the rotation tracking using the hand posture. Therefore, we created an AR rotation knob consisting of three components: a white cylindrical handle, a gray line depicting the rotation axis, an orange tongue, an offset by 60° to show a target rotation, and finally a blue tongue representing the current rotation of the knob (see Figure 2). We opted for this specific offset, as it facilitates high effort to rotate in one go due to joint-rotation constraints [68]. Therefore, users have to make the decision to complete the *Rotation Task* in one go or to regrip. Participants were asked to pinch the white handle with their thumb and index finger. Simultaneous rotation of the hand around the displayed axis allowed them to rotate the knob. They were asked to follow this procedure until the blue and orange tongues aligned.

3.2 Independent Variables

To gain comprehensive insights on which factors could influence the precision and Comfort while interacting with rotational AR tasks, we varied the following factors:

Reach Distance To observe the influence of the distance between the user's body and task, we introduced two depth levels, called *Reach Distance*, based on maximum arm reach. The *far Reach Distance* was defined by users reaching their arm straight to the front without twisting their shoulders. For the second *near Reach Distance*, users were asked to angle their elbow beside their hips and reach forward with just their forearm (see Figure 3a for posture references). The

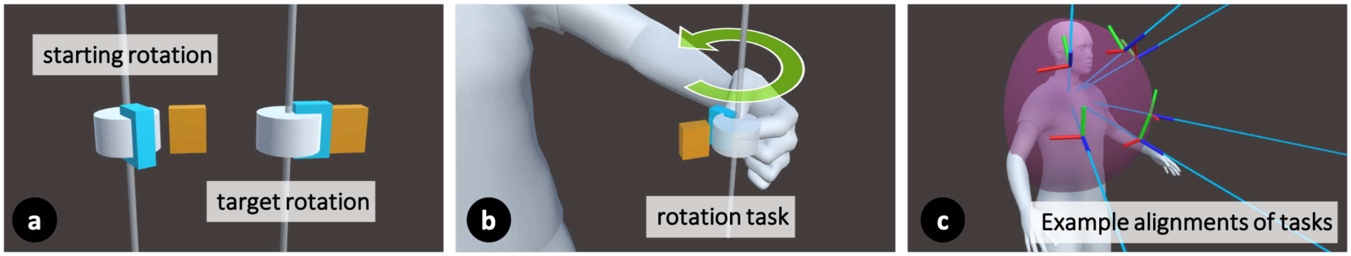


Figure 2: Rotation task during interaction. Participants were asked to (a) rotate a knob from a starting rotation to a target rotation. (b) The knob, therefore, had to be rotated along the depicted axis to align the blue and orange boxes. (c) For each condition, the position of the rotation task was changed to equidistributed points on a half-sphere around the body with the Z-axis defined as the normal vector (blue), the X-axis as the parallel of the spherical surface (red), and the Y-Axis following the meridiancentered axis (green).

depth levels describe two half spheres defining the entire reachable space.

Radius As exploring the whole arm-reachable space for interaction results in an infeasible number of possible locations, we discretized the two half-spherical shaped Reach Distance defined by the *near* and *far Reach Distance* as follows: To keep the time-frame of the user study in a reasonable window, we had to decide on a maximum number of positions to probe. Pretesting revealed users requiring roughly 17 seconds for each trial. For the user study to take around 90 minutes, we, therefore, had the opportunity to probe about 50 to 55 positions. We used Deserno's algorithm to place equidistributed points on a sphere's surface [14] with 52 samples to receive a distribution for a full sphere. Further, we cut the resulting sphere in half to correspond to the half-sphere-shaped arm's reachable space. For our two depth levels, we keep 27 sample points each. This results in a total of 54 sample points inside the reachable space (see Figure 3). This number does not match the initial 52 sample points due to mathematical constraints [14]. For further analysis, we group these points in three different *Radii*: *inner Radius*, *middle Radius* and *outer Radius* (see figure Figure 3b and Figure 3c). Finally, the center of the two half-spheres were positioned between the participant's shoulders. This allowed participants to always be able to reach all positions. *Radius* and *Reach Distance* were anchored to the world and did not follow the participants' movement. We intentionally made this decision to explore the differences for users with limited movement capabilities for the seated Stance and free movement capabilities for the standing Stance (see subsection 3.2 for details).

Task Axis As the task's rotation axes might alter the interaction performance, we further vary three axes of rotation of the task's controls: *X*, *Y*, and *Z*. The Z-axis is defined as the normal vector on the spherical surface. The X-Axis is defined following the parallel of the spherical surface, while the Y-Axis follows the meridian, see Figure 2.

Stance We vary two stances: *seating* and *standing*. Standing allowed our participants to move freely and rotate their whole bodies when performing an interaction. In contrast, when sitting, participants were placed on a bar chair with no backrest and locked orientation. This prevented the participants from rotating their lower bodies and hip, forcing the participants to perform rotations only with their upper body. Namely, this locks one kinematic chain joint in place, increasing the cost of body rotation. Additionally, these stances map to either on-the-go usage, like walking around, and stationary usage, like sitting in a bus or at a table in a confined space.

We varied all four independent variables in a repeated measures design, resulting in $2 \times 27 \times 3 \times 2 = 324$ conditions (Reach Distance × Radius × Task Axis × Stance). This also equals the number of trials per participant. We counterbalanced the order of Stance in a Balanced Latin Square while randomizing Task position and Task axis to prevent learning and fatiguing effects. On average, it took about 90 minutes to complete all trials.

3.3 Dependent Variables

We defined the following dependent variables:

Accuracy Offset between the task's rotating part and target position. Measured in angle offset by degrees.

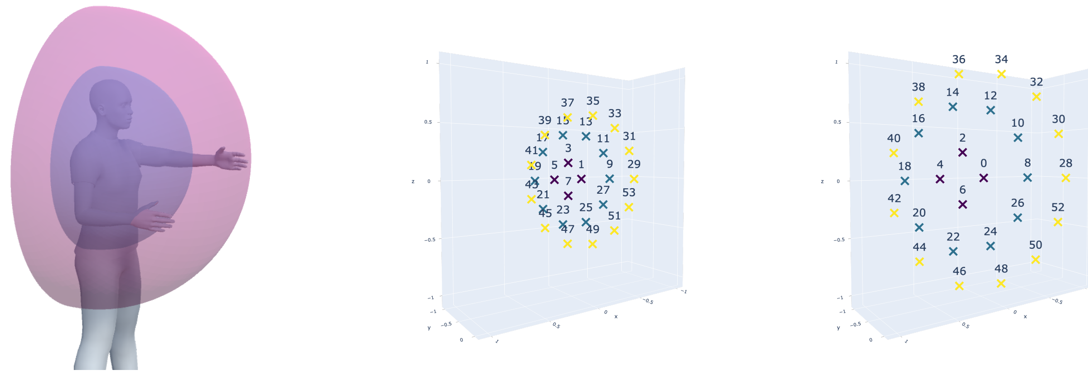
Number of interactions Count of how many times users pinched and released the task before finishing.

Comfort We asked the participants to rate their Comfort level on a 11-point Likert scale (from very low to very high) after each trial, based on a Borg scale [9] as proposed by previous work [33, 62, 74]. We decided to use this quick assessment, as a questionnaire with multiple questions would take too long for the 324 conditions, potentially leading to false reports due to excessive questioning.

Used dominant hand Combined with the demographics, we determined if the interaction was engaged with the participant's dominant hand.

3.4 Study Setup and Apparatus

Our setup consists of two applications: (1) An AR application responsible for rendering the rotation tasks to the users' field-of-view and (2) a desktop application for controlling, logging, and self-assessment of the participants' comfort.



(a) (b) (c)

Figure 3: *Reach Distance* were defined using full- and lower arm length. The center point of the half-sphere was placed between the shoulders, and points were put equidistributed on the surface of a half-sphere [14], building the *far* and *near Reach Distance* with the three *Radii.*

The first application was built using the Unity engine in conjunction with the Mixed Reality Toolkit[1]. It could render the virtual objects (i.e., the knob) directly within the participant’s view using a Microsoft HoloLens 2. Therefore, we designed the rotation knob as described in Chapter 3.1 and used the Mixed Reality Toolkit as the input system. Previous research compared commodity MR glasses tracking accuracy and revealed a high accuracy of the HoloLens 2 compared to other glasses [64]. Therefore, we opted for the HoloLens’ built-in hand tracking [7, 53].

A second desktop application for the operator was responsible for remotely controlling the HoloLens over a TCP socket and logging the quantitative data. This also included the participants’ arms length and posture measurements, used for determining the *Reach Distance*. Therefore, we used an OptiTrack system and mounted a total of seven trackables on the participants’ bodies, as shown in Figure 4. One was used for the HMD tracking on the head, one on each shoulder using a back posture trainer[2], two on the hips using a belt, and one on each wrist using wristbands. Additionally, the controller application also provided an interface for the participants’ self-assessment of their Comfort level after each trial, as described in Section 3.3.

3.5 Procedure

After welcoming the participants, we introduced them to the experiment. Each participant was asked about prior arm, shoulder, and back injuries to ensure they were able to perform the task. Once they reported no injuries and agreed to participate, they were asked to sign a consent form. We then equipped the participants with the seven optical trackables and AR HMD. Then, we calibrated the participants’ full arm length, half arm length, and distance from HMD to their shoulder. Based on the calibration data, the system created the fixed Task positions around the participant (see Figure 3). After the calibration, a short tutorial gave the participants insights into the rotation tasks ahead of them. The system presented three tasks for all three *Task Axis*, followed by tasks at random *Task Positions* just like in the upcoming study. To continue with the next task, the participants had to submit their Comfort into the Desktop application and return to their starting pose, tracked by the OptiTrack system. This ensured that participants started with roughly the same pose for each trial. The participants tested the system freely until they were confident to start the experiment.

To start the experiment, we asked the participants to stand at or sit on a fixed chair with no backrest at the starting position. The experiment was then started via the Desktop application, and the first rotation task was displayed at a randomly chosen position. The participants were free to solve the rotation task however they deemed necessary. No movement restrictions were given except that if the participant were seated, they were to remain seated. When the participants considered a task sufficiently solved, they inputted and submitted a Comfort from 0 to 10 into the Desktop application, indicating they had finished the task. After submitting the Comfort and returning to the previous starting position, the next task was loaded. This cycle continued until all tasks were complete. Afterward, a short break was taken if needed. This concluded half of the experiment. The experiment was then repeated in the opposite Stance with a new random order of tasks.

After completing the entire experiment, the participants filled out a questionnaire asking for demographic data, including their dominant hand, to conclude the experiment. In total, the experiment took about 90 minutes for each participant.

3.6 Participants

We recruited 19 participants (4 female, 15 male) aged between 21 and 30 ($\mu = 23.68$, $\sigma = 2.53$) from the university’s mailing list and among peers. 17 participants reported their right hand as their dominant hand, while 2 reported the left hand, which is in alignment with the world’s proportion of left-handers of around 10% [54, 63]. 12 participants reported no to very little prior AR experience, 2 reported medium experiences, having used AR applications one to

[1]https://github.com/microsoft/MixedRealityToolkit-Unity last visit: September 12th 2023
[2]https://blackroll.com/products/posture last visit: September 12th 2023

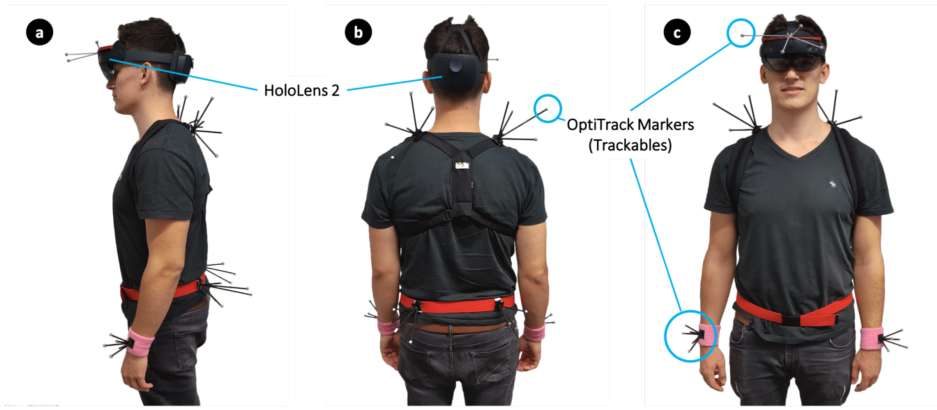


Figure 4: Participant wearing OptiTrack trackers around their hips, shoulders, and arms together with a HoloLens2 HMD from (a) side-, (b) back-, and (c) frontal-view.

three times before, and 5 reported very high experiences, having used AR applications more often. All participants did not report any arm or shoulder musculoskeletal injuries or limitations.

3.7 Analysis

We analyzed the collected data using a four-way Repeated Measure ANOVA with *Reach Distance*, *Radius*, *Task Axis* and *Stance* as factors. Due to the large dataset (6000+ samples), a Shapiro-Wilk test could not be used to test for normality [60, 61]. Therefore, we confirmed the normality using a visual approach using QQ-Plots. For violated normality assumptions, we performed a non-parametric analysis as described below. To test for sphericity, we used Mauchly's test. When the Repeated Measure ANOVA reported significant effects, we applied Bonferroni-corrected t-tests for post-hoc analysis. Further, we report the partial eta-square η_p^2 as an estimate of the effect size using Cohen's suggestions as small ($> .0099$), medium ($> .0588$), or large ($> .1379$) [13, 58]. As a count value for the *Number of Interactions*, we fitted Poisson regression models and applied Type III Wald chi-square tests for significance testing.

4 RESULTS

4.1 Distance to Target

In order to measure the accuracy of participants, we measured the angle between the target rotation and the current rotation of the task's handle. We had to filter out 325 data points (5.3%) due to technical limitations of the Unity Engine (for further details see Appendix A). To remove these incorrect occurrences, we filtered for a measured angle being greater than 0 and smaller than 60, being the initial angle between handle and target rotation. Finally, the *Distance to Target* got log-transformed in order to meet the normality assumption.

Stance, *Reach Distance*, and *Task Axis* showed significant influence on the *Accuracy*. Both, a seating *Stance* and a close-to-the-body interaction, facilitate higher *Accuracy* especially when rotating around the upper Axis.

To investigate whether participants had lower *Accuracy* during later trials, we fitted a linear model on the *Accuracy* and trial count. We could not find a relevant effect with the slope being $m < 0.006$).

Stance The analysis revealed a significant ($F_{1,18} = 13.83$, $p < .01$) influence of the *Stance* with large ($\eta_p^2 = 0.43$) effect size. Post-hoc tests confirmed significantly ($p < .01$) higher *Distance to Target* for *standing* condition ($\mu = 3.9$, $\sigma = 6.57$) compared to *seated* ($\mu = 4.99$, $\sigma = 7.3$), see Figure 5.

Radius Analysis revealed no significant ($F_{1.83,32.99} = 1.18$, $p > .05$) influence of the *Radius* on *Distance to Target*.

Reach Distance We found a significant ($F_{1,18} = 5.89$, $p < .05$) influence of the *Reach Distance* with large ($\eta_p^2 = 0.25$) effect size. Post-hoc tests confirmed significantly ($p < .05$) higher *Distance to Target* for the *near Reach Distance* ($\mu = 4.33$, $\sigma = 7.21$) compared to *far Reach Distance* ($\mu = 4.56$, $\sigma = 6.71$), see Figure 5.

Task Axis The analysis revealed a significant ($F_{1.93,34.82} = 37.1$, $p < .001$) influence of the *Task Axis* with a large ($\eta_p^2 = 0.67$) effect size. Post-hoc tests confirmed significantly ($p < .0001$) higher *Distance to Target* for the z ($\mu = 3.58$, $\sigma = 6.39$) axis compared to x ($\mu = 4.81$, $\sigma = 7.12$) and y ($\mu = 4.93$, $\sigma = 7.26$), see Figure 5.

Interaction effects We observed a significant interaction effect between *Stance* and *Reach Distance* ($F_{1,18} = 10.73$, $p < .01$) and large ($\eta_p^2 = 0.37$) effect size with Post-hoc tests revealing significantly lower *Distance to Target* for *seated Stance* and *far Reach Distance* ($\mu = 5.37$, $\sigma = 7.31$) compared to *standing Stance* and *far Reach Distance* ($p < .01$, $\mu = 3.75$, $\sigma = 5.96$), *seated Stance* and *near Reach Distance* ($p < .05$, $\mu = 4.61$, $\sigma = 7.28$), and *standing Stance* and *near Reach Distance* ($p < .01$, $\mu = 4.05$, $\sigma = 7.13$).

Further, we observed a significant interaction effect between *Stance* and *Task Axis* ($F_{1.99,35.97} = 7.97$, $p < .01$) with a large ($\eta_p^2 = 0.31$) effect size. Post-hoc tests confirmed significantly lower *Distance to Target* for *seated Stance* and *X Task Axis* ($\mu = 5.53$, $\sigma = 7.53$) compared to *standing Stance* and *X Task Axis* ($p < .05$, $\mu = 4.07$, $\sigma = 6.6$), *standing Stance* and *Y Task Axis* ($p < .05$, $\mu = 4.22$, $\sigma = 6.6$), *seated Stance* and *Z Task Axis* ($p < .0001$, $\mu = 3.75$, $\sigma = 6.3$), and *standing Stance* and *Z Task Axis* ($p < .05$, $\mu = 3.4$, $\sigma = 6.47$). Moreover, *standing Stance* and *X Task Axis* ($\mu = 4.07$, $\sigma = 6.6$) had significantly

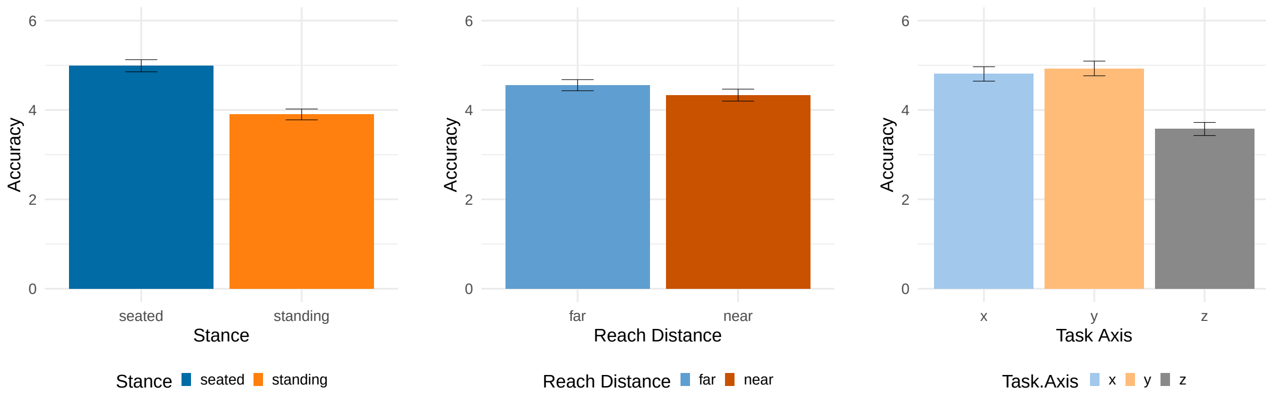


Figure 5: The *Accuracy* in degrees with the according Standard Error for *Stance, Reach Distance,* and *Task Axis.* The error bars depict the standard error.

higher *Distance to Target* compared to *seated Stance* and *Y Task Axis* ($p < .001$, $\mu = 5.64$, $\sigma = 7.81$). Furthermore, *seated Stance* and *Y Task Axis* ($\mu = 5.64$, $\sigma = 7.81$) facilitates lower *Distance to Target* compared to *standing Stance* and *Y Task Axis* ($p < .001$, $\mu = 4.22$, $\sigma = 6.6$), *seated Stance* and *Z Axis* ($p < .0001$, $\mu = 3.75$, $\sigma = 6.3$), and *standing Stance* and *Z Task Axis* ($p < .001$, $\mu = 3.4$, $\sigma = 6.47$). Lastly, *standing Stance* and *Y Task Axis* ($\mu = 4.22$, $\sigma = 6.6$) has a significantly lower *Distance to Target* compared to *standing Stance* and *Z Task Axis* ($p < .05$, $\mu = 3.4$, $\sigma = 6.47$).

4.2 Number of Interactions

As another measurement for efficiency, we counted how many times participants interacted with the task during each condition.

Stance, *Reach Distance*, and *Task Axis* showed significant influence on the *Number of Interactions.* A standing *Stance* as well as near Interaction facilitates lower *Number of Interactions.* Finally, knob rotations around the upper axis required less *Number of Interactions* compared to the other axes.

To investigate whether participants had lower *Number of Interactions* during later trials, we fitted a linear model on the *Number of Interactions* and trialcount. We could not find a relevant effect with the slope being $m < 0.0002$).

Stance The analysis revealed no significant ($\chi^2(1) = 3.36$, $p > .05$) effect of the *Stance* on *Number of Interactions*

Radius The analysis revealed no significant ($\chi^2(2) = 3.25$, $p > .05$) effect of the *Radius* on *Number of Interactions.*

Reach Distance The analysis revealed no significant ($\chi^2(1) = 3.71$, $p > .05$) effect of the *Reach Distance* on *Number of Interactions.*

Task Axis Finally, our analysis revealed a significant ($\chi^2(2) = 9.77$, $p < .01$) effect for the *Task Axis.* The Post-hoc tests showed significantly less *Number of Interactions* for the *Y Task Axis* ($\mu = 1.36$, $\sigma = 0.86$) compared to the *X Task Axis* ($p < .0001$, $\mu = 1.59$, $\sigma = 1.14$) and *Z Axis* ($p < .001$, $\mu = 1.49$, $\sigma = 0.91$), see Figure 6.

Interaction effects The analysis revealed no interaction effects.

4.3 Comfort

We assessed the participant's Comfort while performing the task as described in Chapter 3.3.

Stance, *Radius*, and *Reach Distance* showed significant influence on the *Comfort.* Our participants rated the standing *Stance* with higher *Comfort* than the seated *Stance.* Additionally, the *Comfort* declined from the inner through the middle to outer *Radius.* Lastly, participants rated the near *Reach Distance* with higher *Comfort.*

To investigate whether participants rated lower *Comfort* levels during later trials, we fitted a linear model on the *Comfort* and trialcount. We could not find a relevant effect with the slope being $m > -0.0027$).

Stance The analysis revealed a significant ($F_{1,18} = 9.72$, $p < .01$) effect of *Stance* with large ($\eta_p^2 = 0.35$) effect size. Post-hoc tests further showed significant ($p < .01$) higher *Comfort* for the *standing Stance* ($\mu = 7.46$, $\sigma = 1.98$) compared to *seated Stance* ($\mu = 6.93$, $\sigma = 2.34$), see Figure 7.

Radius The analysis revealed a significant ($F_{1.36,24.56} = 53.21$, $p < .001$) effect of *Radius* with large ($\eta_p^2 = 0.75$) effect size. Post-hoc tests further showed significant lower *Comfort* for the *outer Radius* ($\mu = 6.77$, $\sigma = 2.38$) compared to the *middle Radius* ($p < .001$, $\mu = 7.51$, $\sigma = 1.91$) and *inner Radius* ($p < .001$, $\mu = 7.9$, $\sigma = 1.76$), see Figure 7.

Reach Distance The analysis revealed a significant ($F_{1,18} = 66.79$, $p < .001$) effect of *Reach Distance* with large ($\eta_p^2 = 0.79$) effect size. Post-hoc tests further showed significant ($p < .001$) lower *Comfort* for the *far Reach Distance* ($\mu = 6.75$, $\sigma = 2.35$) compared to the *near Reach Distance* ($\mu = 7.65$, $\sigma = 1.91$), see Figure 7.

Task Axis We observed no significant ($F_{1.35,24.28} = 3.6$, $p > .05$) effect on the *Comfort* for *Task Axis.*

Interaction effects The analysis showed a significant interaction effect between *Stance* and *Reach Distance* ($F_{1,18} = 40.15$, $p < .001$) with large ($\eta_p^2 = 0.69$) effect size with Post-hoc revealing significantly lower *Comfort* for *seated Stance* with *far Reach Distance* ($\mu = 6.24$, $\sigma = 2.42$) compared to *seated Stance* with *near Reach Distance* ($p < .0001$, $\mu = 7.62$, $\sigma = 2.05$),

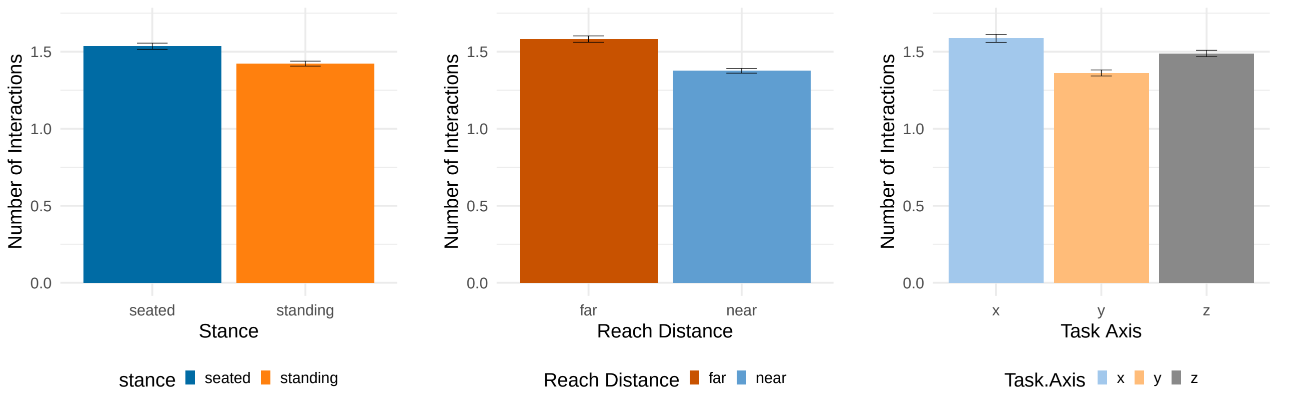


Figure 6: The *Number of Interactions*. The error bars depict the standard error.

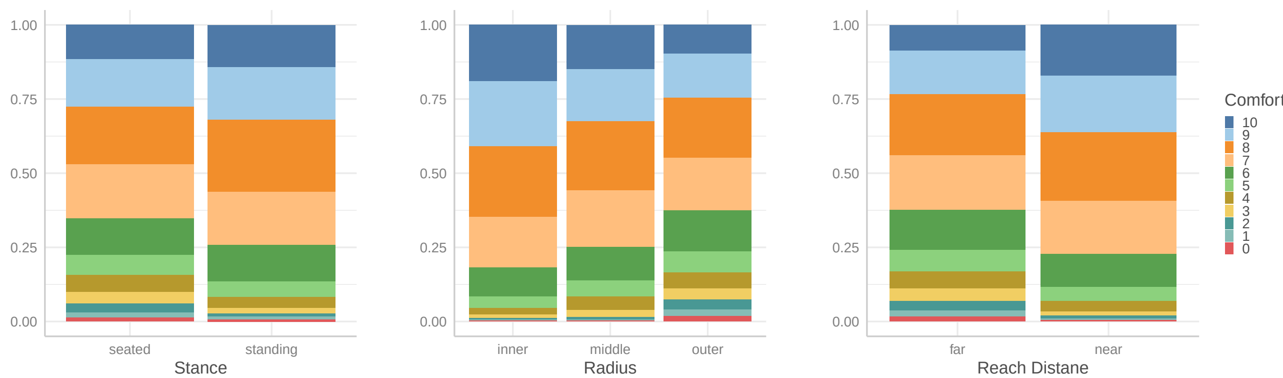


Figure 7: The *Comfort* score with their respective distribution.

standing Stance with *far Reach Distance* ($p < .001$, $\mu = 7.25$, $\sigma = 2.16$), and *standing Stance* with *near Reach Distance* ($p < .0001$, $\mu = 7.67$, $\sigma = 1.76$). Further, *standing Stance* with *near Reach Distance* ($\mu = 7.67$, $\sigma = 1.76$) had significantly higher *Comfort* than *standing Stance* with *far Reach Distance* ($p < .05$, $\mu = 7.25$, $\sigma = 2.16$). Beyond this interaction effect, the analysis revealed a three-way interaction effect between *Stance*, *Radius*, and *Reach Distance* that we omit due to space limitations.

4.4 Used Dominant Hand

The *Horizontal Reach* and *Task Axis* showed significant influence on the usage of the dominant hand. Participants prefere to use their dominant hand in all positions. For the horizontal reach they tend to switch to the non-dominant hand only if the tasks appear to far non-dominant hand side.

Stance The analysis revealed no significant ($\chi^2(1) = 0.08$, $p > .05$) effect of the *Stance* on the probability of *Used Dominant Hand*.

Radius The analysis revealed a significant ($\chi^2(2) = 6.02$, $p < .05$) effect of the *Radius* on the probability of *Used Dominant Hand*. Post-hoc tests further showed significant higher probability for *Used Dominant Hand* for the *inner Radius* ($\mu = 0.7$, $\sigma = 0.46$) compared to the *middle Radius* ($p < .001$, $\mu = 0.65$, $\sigma = 0.48$) and *outer Radius* ($p < .001$, $\mu = 0.65$, $\sigma = 0.48$)

Reach Distance The analysis revealed no significant ($\chi^2(1) = 0.39$, $p > .05$) effect of the *Reach Distance* on the probability of *Used Dominant Hand*.

Task Axis Our analysis revealed a significant ($\chi^2(2) = 6.89$, $p < .05$) effect for the *Task Axis*. The Post-hoc tests showed significantly lower probability for *Used Dominant Hand* for the *Y Task Axis* ($\mu = 0.56$, $\sigma = 0.5$) compared to the *X Task Axis* ($p < .0001$, $\mu = 0.7$, $\sigma = 0.46$) and *Z Task Axis* ($p < .0001$, $\mu = 0.66$, $\sigma = 0.48$). Further, the *Z Task Axis* ($\mu = 0.66$, $\sigma = 0.0.48$) showed significantly ($p < 0.01$) lower probability for *Used Dominant Hand* compared to the *X Task Axis* ($\mu = 0.7$, $\sigma = 0.46$).

Interaction effects The analysis showed a significant interaction effect between *Radius* and *Stance* ($\chi^2(2) = 6.26$, $p < .05$). Post-hoc tests revealing lower probability for *Used Dominant Hand* for the middle *Radius* and seated *Stance* ($\mu = 0.6$, $\sigma = 0.5$) compared to inner *Radius* and seated *Stance* ($p < 0.05$, $\mu = 0.67$, $\sigma = 0.47$), inner *Radius* and standing *Stance* ($p < 0.0001$, $\mu = 0.74$, $\sigma = 0.44$), middle *Radius* and standing *Stance* ($p < 0.001$, $\mu = 0.7$, $\sigma = 0.46$), and outer *Radius* and

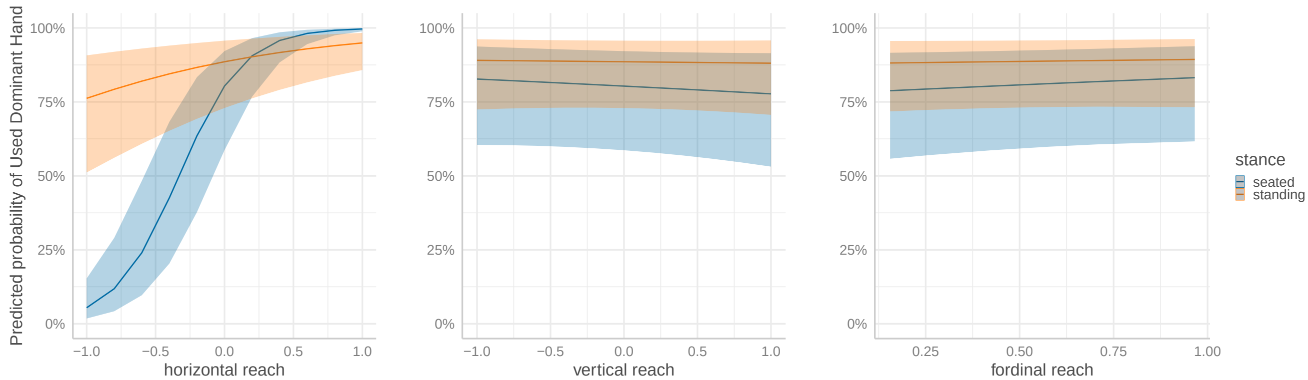


Figure 8: The probability of using the dominant hand for task location. For the x axes, -1 depicts a full arm length to the non-dominant hand side, while 1 depicts a full arm length to the dominant hand side. The forward reach is limited between 0 and 1, because we did not explore the space behind participants.

standing *Stance* ($p < 0.0001$, $\mu = 0.72$, $\sigma = 0.45$). Further, the outer *Radius* and seated *Stance* ($\mu = 0.58$, $\sigma = 0.5$) showed lower probability for *Used Dominant Hand* compared to inner *Radius* and seated *Stance* ($p < 0.01$, $\mu = 0.67$, $\sigma = 0.47$), inner *Radius* and standing *Stance* ($p < 0.0001$, $\mu = 0.74$, $\sigma = 0.44$), middle *Radius* and standing *Stance* ($p < 0.001$, $\mu = 0.7$, $\sigma = 0.46$), and outer *Radius* and standing *Stance* ($p < 0.001$, $\mu = 0.72$, $\sigma = 0.45$).

Because the fitted generalized linear mixed-effects model could handle continuous values, we in addition switched *Radius* and *Reach Distance* for their respective continuous coordinates in the reachable space to gain a deeper understanding of the reachable space. Therefore, we introduced the *Horizontal Reach*, representing the axis spanning from the most distant reachable point on the non-dominant hand side to the most distant reachable points on dominant hand side. Similar to the *Vertical Reach*, spanning from the most bottom reachable point to the most top reachable point. Lastly, *Fordinal Reach* ranges from the center of the body to the most forward reachable point. We only report significant effects in the following:

Horizontal Reach The analysis revealed a significant ($\chi^2(1) = 80.58$, $p < .001$) effect for the *Horizontal Reach*.

Stance The analysis revealed a significant ($\chi^2(1) = 7.76$, $p < .01$) effect for the *stance* and *Horizontal Reach*. The Post-hoc tests showed significantly ($p < .0001$) lower probability for *Used Dominant Hand* for the *seated Stance* ($\mu = 0.6$, $\sigma = 0.49$) compared to the *standing Stance* ($\mu = 0.71$, $\sigma = 0.45$).

Task Axis Our analysis revealed a significant ($\chi^2(2) = 11.37$, $p < .01$) effect for the *Task Axis*. The Post-hoc tests showed significantly lower probability for *Used Dominant Hand* for the *Y Task Axis* ($\mu = 0.6$, $\sigma = 0.5$) compared to the *X Task Axis* ($p < .0001$, $\mu = 0.7$, $\sigma = 0.46$) and *Z Axis* ($p < .0001$, $\mu = 0.66$, $\sigma = 0.48$). Further, the *Z Task Axis* ($\mu = 0.68$, $\sigma = 0.47$) showed significantly ($p < 0.05$) lower probability for *Used Dominant Hand* compared to the *X Task Axis* ($\mu = 0.7$, $\sigma = 0.46$).

Interaction effects The analysis revealed a significant ($\chi^2(1) = 32.75$, $p < .001$) effect for the *Stance* and *Horizontal Reach*. Post-hoc tests further showed a higher sensitivity for the *seated Stance* ($\beta = -3.93$) compared to the *standing Stance* ($\beta = -1.01$) and for the *Horizontal Reach*, see Figure 8. The analysis revealed a significant ($\chi^2(2) = 11.28$, $p < .001$) effect for the *Task Axis* and *Horizontal Reach*. Post-hoc tests further showed a higher sensitivity for the *X Task Axis* ($\beta = 2.91$) compared to the *Y Task Axis* ($\beta = 2.09$) and *Z Task Axis* ($\beta = 2.55$).

5 DISCUSSION

We discuss our findings and derive implications for future AR rotational mid-air interactions.

5.1 Keep Interactions Close when the Body Movement is Limited

Previous research showed that the space close to the user's body is highly ergonomic and should be primarily used for interaction [4, 18, 24]. With our rotation task, we observed the same behavior. While *standing*, the *Comfort* improved by 7.03% when interacting on the *near interaction Reach Distance* compared to the *far interaction Reach Distance*. This effect was even more substantial while *seated*, increasing the *Comfort* by 22.12% when interacting on the *near Reach Distance*. On the one side, it indicates that participants made use of their increased freedom while *standing* to move their body for more comfortable interaction. It also confirms previous research on the importance of close-to-body interaction. We further found the same behavior for the *Accuracy*. The *Accuracy* improved 8% when moving the interaction from the far *Reach Distance* to the close *Reach Distance* while *seated*.

This shows the importance of keeping the interaction close to the body as long as possible. While we observe this negative effect for *standing* and *seated*, the letter stance suffers from far worse effects. Therefore, it is essential to keep rotational interaction close when you are in settings with limited freedom of movement. We hypothesize that users subconsciously reallocate the tasks to more comfortable and accurate locations when *standing* by moving their whole body. This also emphasizes that holding the arm in extended postures facilitates more discomfort than moving the whole body. Therefore, proofing the severeness of close body interaction.

5.2 Interactions Further Away from the Body Are Precise

While we already saw the decrease of *Comfort* for interactions further away from the body, they can be comparably accurate. Our results indicate that users use their unconstrained *standing Stance*, resulting in good accuracy, even for interactions far away. Participants achieved comparable accuracy when interacting on the *far Reach Distance* compared to the *near Reach Distance*, but only while *standing*. However, the comparable accuracy does come at the cost of about 5.79% lowered *Comfort* levels.

This indicates that participants used their freedom not to be stationary to achieve higher accuracy but simultaneously lower their *Comfort* perception. While user interface designers could place rotation tasks further away for on-the-foot or standing scenarios, they should consider this tradeoff and not move frequently used tasks to a further Reach Distance [8]. However, if space is limited in the closer interaction space, or the task is used infrequently, designers can relocate this task further away from the user without sacrificing accuracy.

Our tasks required users to be as precise as possible with a continuous input range. It would be interesting to further investigate this effect for rotational tasks with lower fidelity, like tasks with discrete input range, to explore if users would still exploit their freedom to move.

5.3 Rotate Around the Upper Axis to Reduce the Number of Required Interactions

We observed the lowest *Number of Interactions* for the *Y Task Axis*, being 8.72% lower compared to *Z Task Axis* and 14.47% to *X Task Axis*. Considering the absence of significant effects in *Comfort* between the *Task Axes*, we argue that the physiology allows users to rotate the knob around the *Upper Axis (Y Task Axis)* more quickly and farther. This allows them to reach the desired rotation more efficiently by not having to re-grip the knob to rotate it further.

We observed this effect even with a relatively small rotation of only 60° that had to be performed. It would be interesting to explore the benefit of an upright rotation axis for tasks with more rotation to overcome.

5.4 Good Element Visibility Does not Imply Fewer Interactions

By design of our rotation task, the *Z Task Axis* has a visibility advantage over the other axes. Due to the egocentric alignment of the axes, see Figure 2, the *Z Task Axis* have the advantage of following the line of sight precisely. This allows for a clear top-down view of the knob. Users can see the knob's tongue and target without perspective distortion. While we tried to keep this effect as low as achievable, it was impossible to eliminate it. We observed a significantly higher accuracy for the *Z Task Axis* compared to the other axes. This is caused by better visibility, allowing users to be more precise.

However, as mentioned before, the lowest *Number of Interactions* was achieved by the *Y Task Axis*, being 8.72% lower compared to the *Z Task Axis*. At the same time, *X Task Axis* and *Z Task Axis* had no significant differences for their *Number of Interactions*. Although *Z Task Axis* has better visibility, participants needed to re-grip comparably to the *X Task Axis*, not having a visibility advantage.

We conclude that better visibility does not imply fewer *Number of Interactions*. To reduce the number of interactions effectively, designers should consider the *Y Task Axis* as orientation for their rotation tasks.

5.5 Utilize the Non-Dominant Hand

Users generally prefer to use their dominant hand whenever possible. This can be observed in the standing *Stance*. Even for the task locations furthest on the non-dominant hand side, participants used their dominant hand for about three-quarters of the interactions. However, this behavior changes when seated. Participants started to use their non-dominant hand more often than their dominant hand once the tasks were to the outer side of their non-dominant shoulder. This indicates that users would instead turn and move their whole body before using the non-dominant hand for rotational tasks. However, making it difficult to do so, participants start to use their non-dominant hand more often than their dominant one once the tasks are placed far enough to the non-dominant hand side. This effect can be exciting when designers want to enforce the use of the non-dominant hand, e.g. if the dominant hand is currently occupied. Users would use the secondary hand over switching objects between their hands.

6 LIMITATIONS AND FUTURE WORK

Our results revealed valuable insights into mid-air Rotation Interaction in AR Environments. However, this work has some limitations discussed in the following.

6.1 Validity

To explore the ergonomics of rotational mid-air interactions in AR, we conducted a controlled experiment, as this allows us to explore fundamental properties. However, a controlled experiment with limited participants does not generalize to the whole world's population. As such, the results presented here are mainly generalizable to the user group of young adults and may vary for different user groups like children or seniors. Individual factors, such as varying physiology and user expectations towards an interaction [37] may lead to different research results.

Furthermore, we have to consider technical limitations. While the HoloLens 2 is considered state-of-the-art technology while performing our study, it is affected by tracking inaccuracies. The tracking performance is strongly dependent on the physical characteristics of the hand, such as hand size or shape [66]. With more accurate tracking and stable vision, the results could vary from our findings. We decided to use the HoloLens' markerless tracking system rather than OptiTrack because participants in explorative studies during development had complained about the additional hardware on the fingers and reported increased fatigue and discomfort due to the added weight. Although the tracking hardware was designed to be as light as possible, this low weight is already very noticeable in a negative way. This negatively influenced the *Comfort* over time. Previous research compared commodity MR glasses accuracy and revealed a high accuracy of the HoloLens 2 compared to other glasses [64]. Therefore, we opted for the HoloLens’ built-in hand tracking [7, 53]. We instructed our participants to report any issues they encountered, including tracking issues. Besides three incidences where the HoloLens overheated, we did not encounter any issues.

For future work, it might be worthwhile to measure an additional metric, to differentiate between “Number of Attempted Hand Interaction” and “Number of Interactions” as proposed by Lauer et al. [42].

6.2 Properties of Mid-Air Gestures

We decided to opt for a user-centered *Task Axis* alignment, with the axis following a sphere’s surface (see Figure 2). Future work will explore other alignments, such as fixing the *Y Axis* to the real world’s up axis, being opposite direction to gravity. In this study, we explored rotational tasks with a 60° offset. This value was selected to impose a regrip decision-making on the user. Varying this offset to higher or lower numbers is of interest for future work since it influences the user’s grip [22] and regrip decision-making.

Similar to the rotation offset, our study did not enforce and explore the rotation direction. In our study, we did not tell participants which direction to rotate the knob. However, users may develop individual preferences for gesture interaction to improve the gesture recognition (e.g., in the domain of smart homes and assisted living [38, 39]). In future work, we will investigate the preferred ergonomic rotation direction.

6.3 Fatigue

While our participants had plenty of rest during the experiment, we must consider the influence of fatigue for later trials. We tried to lower carry-over effects for fatigue with counterbalancing and randomization. After the experiment, participants reported that they could still go on with more mid-air AR interactions. However, future research can focus on alternative sensing strategies, such as electromyography, to assess muscle fatigue and discomfort in real-time [30, 31]. Still, we must consider the influence of physical and cognitive fatigue [36] on our findings.

Related to that, we had to close down on independent variables. Varying *Stance*, *Reach Distance*, *Radius*, and *Task Axis* our participants needed about 90 minutes to complete all trials. Introducing more variables and conditions, like proposed in Chapter 6.2, would have resulted in an exponential growth of study length, introducing unwanted fatigue.

7 CONCLUSION

In this paper, we highlighted the importance of a thoughtful positioning of AR interface elements to ensure optimal ergonomics for users. In a controlled experiment, we assessed the accuracy, Comfort, and number of interactions within the user’s reachable space to gain better insights into ergonomics during rotational interactions. As part of our results, we found that such interactions were significantly more beneficial for high Comfort levels when close to the body, particularly in a seated position. Additionally, rotations around the upper axis (*Y Task Axis*) facilitate fewer interactions, suggesting more ergonomic rotations compared to rotations around the other axes (*X Task Axis*, *Z Task Axis*). In summary, our results could demonstrate essential factors for future rotation-based AR interfaces, which are highly usable and provide more healthful ergonomics for users.

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A INACCURATE ANGLE CALCULATION BY UNITY ENGINE

To analyse and evaluate the accuracy of the participants the angle between the current rotation and the target rotation was calculated. Therefore, as Unity suggests[3], we used their internal *Quaternion.Class*. The given function *Quaternion.Angle*, a commonly used function[4], was used to calculate the angle. This resulted in inaccurate calculations, when the angle between the current rotation and the target rotation was close to 0 degrees (indicating a very high accuracy). Inspection of the code of the *Quaternion.Angle* function[5] revealed an implemented tolerance for small angles causing the function to prematurely return 0 degrees. Further, the inspection revealed *acos* being used to calculate the angle. In multiple discussions it was reported, that *acos* is sensitive to errors in situations where the scalar part of the quaternion product is close to unity [6] [7] [8], which is the case for small angles. Consequently, Unity Engine's internal calculations of an angle between two quaternions are inaccurate for small angles.

[3]https://docs.unity3d.com/Manual/class-Quaternion.html
[4]https://docs.unity3d.com/ScriptReference/Quaternion.html
[5]https://github.com/Unity-Technologies/UnityCsReference/blob/master/Runtime/Export/Math/Quaternion.cs
[6]https://researchgate.net/post/How_do_I_calculate_the_smallest_angle_between_two_quaternions
[7]https://stackoverflow.com/questions/21513637/dot-product-of-two-quaternion-rotations
[8]https://de.mathworks.com/matlabcentral/answers/101590-how-can-i-determine-the-angle-between-two-vectors-in-matlab

Instead of the default out of the box implementation of the Unity Engine, we highly encourage researchers to use Unity.Mathematics[9] in the future.

[9]https://github.com/Unity-Technologies/Unity.Mathematics/blob/master/src/Unity.Mathematics/quaternion.cs