# Bumpy Ride? Understanding the Effects of External Forces on Spatial Interactions in Moving Vehicles

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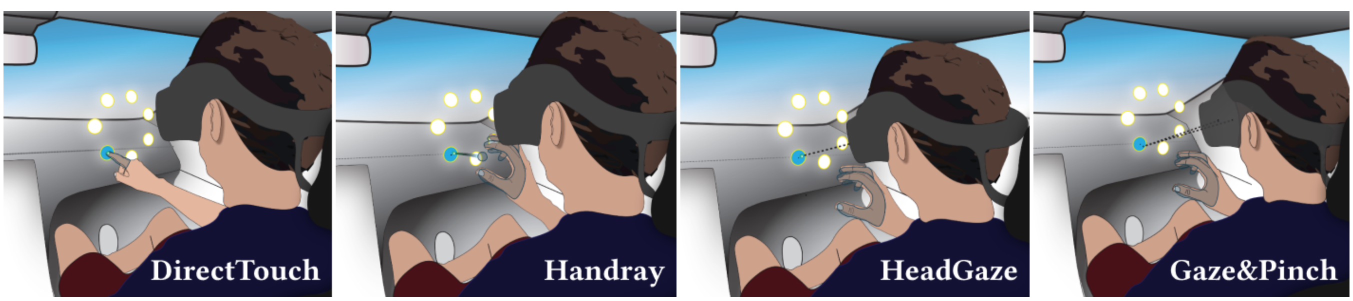


**Figure 1: We investigate the effects of external forces in a moving vehicle on spatial interactions in the context of in-car augmented reality using a Fitts' law task. The methods are, from left to right, DirectTouch, Handray, HeadGaze, and Gaze&Pinch.**

## Abstract

As the use of Head-Mounted Displays in moving vehicles increases, passengers can immerse themselves in visual experiences independent of their physical environment. However, interaction methods are susceptible to physical motion, leading to input errors and reduced task performance. This work investigates the impact of G-forces, vibrations, and unpredictable maneuvers on 3D interaction methods. We conducted a field study with 24 participants in both stationary and moving vehicles to examine the effects of vehicle motion on four interaction methods: (1) Gaze&Pinch, (2) DirectTouch, (3) Handray, and (4) HeadGaze. Participants performed selections in a Fitts' Law task. Our findings reveal a significant effect of vehicle motion on interaction accuracy and duration across the tested combinations of Interaction Method × Road Type × Curve Type. We found a significant impact of movement on throughput, error rate, and perceived workload. Finally, we propose future research considerations and recommendations on interaction methods during vehicle movement.


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## CCS Concepts

• **Human-centered computing → Mixed / augmented reality**; **Field studies**; **Empirical studies in HCI**; **Empirical studies in interaction design**; • **Applied computing → Consumer health**.


## Keywords

in-car, Mixed Reality, augmented reality, automotive, interaction, human factors, field study, machine learning

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## 1 Introduction

In 2022, workers in the US commuted for ≈230 hours to and from work [85]. Commuting time negatively affects well-being [21, 72] due to the limited possibility of engaging in meaningful activities. However, with automated vehicles (AVs), commute times could be used to perform non-driving related tasks (NDRT). This will enable former drivers to use the freed-up time to work [55], watch movies, or even sleep [24]. In a survey by Mathis et al. [55], 58.8% of the participants indicated that they could imagine using the newly gained time to perform work-related tasks. Due to the current commuting behavior, 60.7% state that they do not usually use this time for work-related tasks. Current challenges hindering work-related tasks include manual driving, lack of infrastructure for connectivity, and privacy in public transport [55].

Using augmented reality (AR) and virtual reality (VR) Head-Mounted Displays (HMD) during commutes enables users to engage in working tasks, freely customize their environment, and keep content private. Layouts can also be adapted to task-specific requirements and respect user-based ergonomics to ensure an optimal working environment [58]. However, the display of digital content at head level can disrupt the visibility of the surrounding environment. This can lead to users experiencing increased symptoms of motion sickness (MS), as visual motion perception is reduced [28, 78].

HMDs are currently still in their development but are starting to mature with notable launches of the Apple Vision Pro [43] and the Meta Quest 3 [60]. The experiences available could inspire users to try using such devices during commutes, such as watching movies on large virtual screens. Meta aims to bring the Quest 3 into vehicles[1] and multiple car vendors have conducted research on using HMDs in their vehicles [1, 8, 32, 33, 38]. To engage in NDRTs, interactions within the vehicle are necessary. These occur while standing, for example, at a traffic light, or during movement [3, 22, 57]. Here, multiple driving-related factors such as G-Forces, vibrations, dynamic lighting, unpredictable maneuvers, and the constrained space within the vehicle present challenges for passengers to efficiently use HMDs during commutes. While previous work has already shown effects of this motion in simulators with HMDs [22] and for touch-screen interaction [57], an evaluation of HMD-relevant interaction methods in a real-world setting is missing.

In a within-subject study with *N*=24 participants, we evaluated interaction methods that do not require proprietary hardware other than the headset. We evaluated the interaction methods *Gaze&Pinch, DirectTouch, Handray*, and *HeadGaze* using a Fitts' Law task. The impact of vehicular motion on interactions was analyzed regarding task performance, perceived workload, system usability, motion sickness, perceived safety, and trust using standardized questionnaires. Furthermore, we identified patterns between vehicle movement and interaction errors. In this work, we answer the following research questions (RQs):

– **RQ1** *What impact does vehicle motion have on perceived workload, usability and task performance for the interaction methods regarding selection tasks?*
– **RQ2** *Which type of vehicle motion (i.e., standstill, bumpy road, long-curve, short-curve) impacts the evaluated interaction methods significantly?*
– **RQ3** *How should the interaction methods Gaze&Pinch, DirectTouch, Handray and HeadGaze be adapted, considering their usage within a moving vehicle?*

*Contribution Statement:* This study (1) investigated the interactions *Gaze&Pinch, DirectTouch, Handray* and *HeadGaze* employable for AR and VR HMD applications in moving and standing contexts. Expanding on this, (2) the collection of sensor data and subsequent labeling into three road and curve types, allowed for the assessment of selection precision and time for each combination of Interaction Method × Road Type × Curve Type. This enabled a detailed analysis of how the interaction methods performed during each combination. Additionally, (3) we performed semi-structured interviews to gather qualitative data on using these interaction methods in moving vehicles. Finally, (4) we propose a set of guidelines with recommendations on interaction methods for selection tasks during vehicle movement, and considerations for future research.

The results help define which interaction method should best be used during movement, with the assessment of the impact of road and curve types during vehicle movement on eye-tracking-based interactions being an additional novelty.

## 2 Related Work

In the following, we introduce general input modalities in the automotive context, provide an in-depth description of AR and VR interaction, and discuss motion effects on interaction.

### 2.1 Input Modalities in Vehicles

Vehicle interfaces commonly utilize input modalities such as touch, gaze, and gestures, particularly in the front area, where interaction is most frequent [44]. Previous studies on AVs explored the use of touch panels for drivers to initiate maneuvers at the automation limit [88, 89] or to select specific AV maneuvers, such as lane changes [47]. These touch panels were typically placed either on the steering wheel [29, 52, 68] within the center/middle console [3, 19, 65, 76, 87], or on a separate tablet [23]. Hand gestures were also used for maneuver-based intervention [23, 26] and

[1] Meta and BMW: Taking AR and VR Experiences on the Road. https://about.fb.com/news/2023/05/meta-bmw-ar-vr-experiences/; Accessed 22.08.2024

lateral and longitudinal motion [54]. Similarly, Rümelin et al. [76] and Colley et al. [23] utilized free-hand pointing gestures for input, while Fujimura et al. [31] employed hand-constrained pointing gestures. Eye-gaze as a standalone input was utilized by Poitschke et al. [71] for referencing or selecting objects [64, 75]. Additionally, multimodal input was employed to address the challenges associated with unimodal interaction. For instance, gaze was used to localize the target, while hand gestures were used to coordinate pointing [20, 49, 74]. Speech input has been implemented to facilitate driver-vehicle cooperation and to select vehicle maneuvers [6]. For instance, Roider et al. [75], Neßelrath et al. [64], and Sezgin et al. [80] examined the use of speech commands for selecting objects within the vehicle. However, voice input may be less effective in noisy environments (e.g., during group conversations), and drivers may have limited trust in speech recognition systems or may become confused about the appropriate commands needed to initiate the desired actions [12, 26].

Most studies were conducted using low-fidelity driving simulators without motion feedback (e.g.,[36, 73–76]). However, the vehicle motions induced by road and driving conditions likely impact the results significantly. They may alter the considerations for real in-vehicle interaction proposed in these studies. This is particularly important for studies that measure interaction precision [36] or completion time [65].

## 2.2 Interactions in Augmented and Virtual Reality in Vehicles

Performing mid-air interactions in moving vehicles introduces a distinct set of challenges, stemming primarily from unpredictable vehicular motion. Prior research investigated the usage of touchscreens in moving vehicles [2, 3, 5, 57, 66], with studies such as those performed by Mayer et al. [57] and Ahmad et al. [2, 3] having specifically investigated the impact such movements have on touchscreen interactions. Ahmad et al. [2] state that road perturbations and vehicle motion can increase erroneous selections. Furthermore, they state that this behavior requires drivers to dedicate more time to performing selection tasks, potentially diverting attention from driving and raising safety concerns. Mayer et al. [57] further explored this topic by using a motion simulator, investigating the effects of road bumps on touchscreen interactions under varying vehicle speeds. They identified a significant reduction in selection accuracy, with vehicle speed not influencing task performance. Furthermore, previous research has considered various aspects like input prediction [2, 57] and multimodal input [74] to improve the usability of such interactions.

However, only limited research was conducted regarding the investigation of interactions performed within AR or VR in vehicle contexts [22, 46, 79, 83]. Studies by Tseng et al. [83], and Kari and Holz [46] investigated interaction methods that improve interactions within constrained spaces persisting within cars. Colley et al. [22] used a 1-Degree of Freedom (DoF) motion platform to investigate common interaction methods such as touch, speech, gesture and eye-gaze input in VR regarding task performance. They found that movement negatively affected task performance for eye-gaze and gesture, with touch and speech remaining largely unaffected. Furthermore, Schramm et al. [79] investigated multiple interaction methods performed within AR regarding workload, usability, and task performance in a moving vehicle. They found Eye-Gaze with a hardware button as the selection method to be the fastest interaction methods, providing the lowest workload. HeadGaze techniques featured low error rates and a comparably low workload. Hand-pointing with a gesture as confirmation was described as highly frustrating for participants and featured high physical demand.

## 2.3 Effects of Vehicle Motion on Interaction

According to Hock, Colley et al. [42], motion and visual fidelity dimensions are essential to classify approaches on the Simulator Continuum. Motion fidelity can range from no motion over motion cues to using a real vehicle. Visual fidelity can range from a 2D screen to the real world. While studies in the real world naturally exhibit the highest external validity, reproducibility or specific situations might only be possible in simulators. Therefore, Colley et al. [22] introduced the SwiVR-Car-Seat, representing longitudinal and lateral vehicle dynamics using a 1-DoF rotation. In the SwiVR-Car-Seat, vehicle dynamics in curves are also matched to the chair's rotation; however, it cannot provide simultaneous motion feedback for both longitudinal and lateral dynamics. Thus, the VAMPIRE by Hock, Colley et al. [42] introduces a 2-DoF approach where a wheelchair drives in circles to simulate motion forces.

Additionally, on-road driving simulation [17, 34, 35, 59] and the use of a Wizard-of-Oz (WoZ) driver to control the vehicle [9, 27] have been proposed. However, these works have not yet used these setups to evaluate the effects of motion on interaction but for visualization purposes only.

Regarding interaction effects of motion, Ng and Brewster [65] compared pressure input and haptic feedback for in-car touchscreens between a low-fidelity driving simulator and a real vehicle, finding that while accuracy was similar, selection time was worse in the real vehicle. Similarly, Ahmad et al. [3] showed that vehicle motion increases the effort required for selection. Similar findings were also found by Goode et al. [37], Kim and Song [48], Salmon et al. [77].

# 3 User Study: Understanding External Forces

To answer the RQs, a within-subject user study with 24 participants was conducted. We varied the interaction method (Gaze&Pinch, DirectTouch, Handray, and HeadGaze) and the movement (standstill, movement).

## 3.1 Interaction Methods

This section describes the evaluated interaction methods, focusing on approaches for selecting near objects in virtual environments. According to Hertel et al. [40], selecting near objects usually involves the collision of a handheld controller or the hand itself with the virtual object. For more distant objects, techniques based on ray-casts are used, originating from the user's head, eyes, or hand. They may require a secondary confirmation step. Building on this and previous studies focusing on AR/VR interaction research in vehicles [22, 79], we investigate (1) Gaze&Pinch, (2) DirectTouch, (3) Handray, and (4) HeadGaze as interaction methods (see Figure 1). Each method offers a different approach to user interaction, allowing us to assess various aspects of usability and responsiveness. For the implementation, we used Unity 2022.3.34f1 along with XR Interaction Toolkit (XRI) 2.5.4, XR Hands 1.4.1, and the Unity Ultraleap Tracking Package 6.15.1 with the tracking service 6.0.0 (Hyperion). For immediate feedback, selected objects in the environment responded visually by changing colors from white to red (see Section 3.4). We validated the usability of all interaction methods by performing internal tests with three participants from our institution, including trials with prescription glasses to ensure the functionality of Gaze&Pinch.

*3.1.1 Gaze&Pinch.* The user moves their eyes to focus on an object or interface element they wish to select and then confirms the selection by performing a pinch gesture with the dominant hand [62, 70]. Gaze&Pinch allows for quick and natural targeting, as humans can swiftly shift their attention by moving their eyes, far quicker than moving a cursor with a traditional input device [70]. We continuously monitor the user's gaze, identifying the point in the environment the user is looking at and highlighting potential interactive objects. We did not implement a visual representation of the cursor for Gaze&Pinch, as Sidenmark and Gellersen [81] suggests it to be distracting, especially when it follows every eye movement. Visual feedback was limited to the colored highlighting of the targets.

*3.1.2 DirectTouch.* For the implementation of DirectTouch, we utilized the XR Poke Interactor of the XRI. When the user's dominant index finger pokes a virtual object, it starts following the finger tip regarding depth, is visually highlighted, and becomes selected when the user releases the virtual object thereafter. In line with Kim and Xiong [50], Speicher et al. [82], we used protrusion of virtual objects to improve the sense of reality and spatiotemporal perception during interactions. This behavior mimics the push of a physical button, making it natural and easy to learn, potentially increasing the feeling of presence and immersion.

*3.1.3 Handray.* Handray uses a ray projection from the user's dominant hand for object selection and was implemented using the XR Ray Interactor. To address precision issues of ray projection and user hand movements, we applied smoothing by using the XR Transform Stabilizer to compensate for the Heisenberg effect in spatial interaction [91]. The ray extends from the center between the thumb and index finger until it reaches the target object or a predefined distance (10m), while a pinch gesture confirms the selection. This method combines intuitive pointing with a simple, natural gesture for confirmation, providing a seamless and user-friendly interaction experience.

*3.1.4 HeadGaze.* HeadGaze was implemented with the XR Gaze Interactor. The system tracks the user's head movements and emits a raycast in the direction of gaze. The cursor is placed in the center of the view, which has to be aligned with the target object for selection. A pinch gesture confirms the selection.

## 3.2 Apparatus & Test Environment

The study took place in a midsize-estate, with participants seated in the front passenger seat. The vehicle was equipped with a Varjo XR-3 HMD and a 6-DoF tracking system implemented using middleware

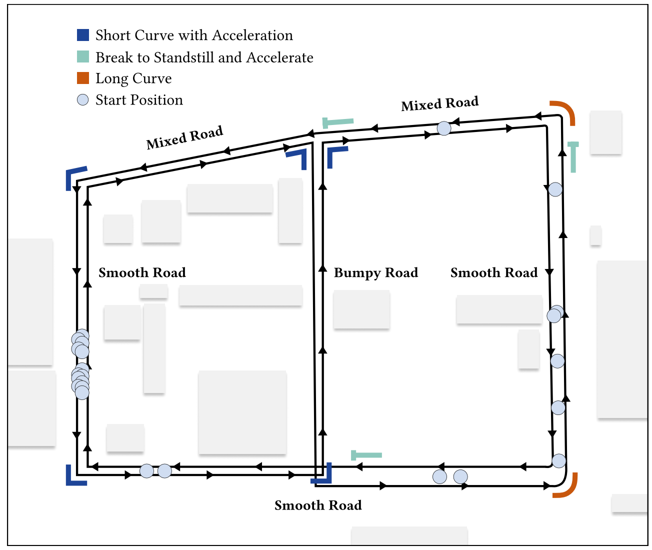



**Figure 2: Route, instructions, and starting positions for all 24 participants. 30km/h is the standard speed employed on the course.**

by LP-Research [67]. An additional IMU was fixed to the vehicle's dashboard in front of the co-driver and used for data recording. Hand tracking was implemented using an Ultraleap Leap Motion 2 attached to the front of the HMD with a 15° downward-facing angle. As we performed a field study, outdoor lighting conditions could vary across participants, from high sunlight exposure to cloudy and rainy days. We, therefore, utilized Ultraleap's *Hinting API* to ensure stable tracking of users' hands across weather conditions. The parameters can be obtained from Appendix B.

We investigated two driving scenarios, namely standstill and movement, with each interaction method performed during each scenario. Therefore, our study design includes the independent variable interaction method with four levels and movement condition with two levels, resulting in a $4 \times 2$ within-subject study.

The course was set in a traffic-calmed environment. We employed a reproducible driving style across all conditions to ensure internal validity [63]. All participants were driven by the same driver who performed preliminary training of the course to ensure a uniform driving style [45]. We used a speed limiter to ensure a uniform maximum speed of 30km/h. The course featured an equal number of directory turns and straight parts to ensure equal driving style variation (see Figure 2). In total, one round along the course featured three sharp curves and two long-curves in each direction, two straight areas in which the vehicle was brought to a standstill (braking) and then accelerated to 30km/h again. One of the long-curves was always driven with a steady speed of 30km/h, while the second one contained parallel acceleration from 0km/h to 30km/h. This acceleration behavior was also applied to short-curves along the route. Furthermore, road conditions (see Figure 5) differed across the route, containing a paved road with close to no bumps (*SmoothRoad*), a section with a bumpy road containing multiple potholes (*BumpyRoad*), and a third section which could be described as a mixture of the previous two (*MixedRoad*).

Figure 4 visualizes the motion profile (vibrations, accelerations) of the road conditions recorded using the IMU specified in Section 3.6. This IMU was mounted on the dashboard in front of the co-driver, so that the x-axis was parallel to the vehicle's forward direction, the y-axis was orthogonal to the vehicle's forward vector, and the z-axis represented vertical acceleration (e.g., road bumps). The start position was randomized per participant, as far as possible considering the road and traffic conditions. This was performed to vary the timing and sequence of the road condition occurrences, thus alleviating, for example, fatigue symptoms occurring at similar points.

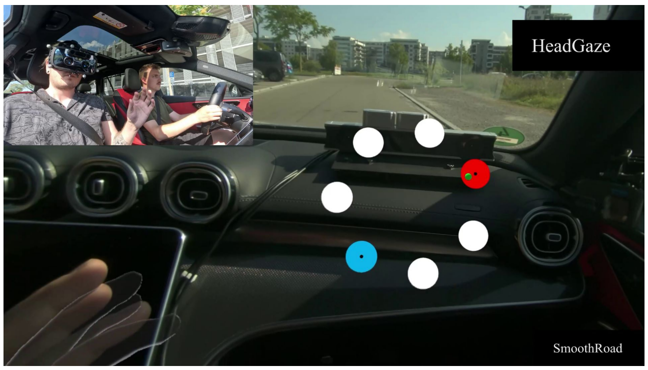



**Figure 3: Fitts' Law Task as observed through the Varjo XR-3 with passthrough enabled. The cursor of each interaction method is shown in green and highlights targets in red when hovering, indicating the ability to select the target. One of the seven targets is always highlighted in blue to indicate it should be selected next, until a successful selection is performed.**

## 3.3 Procedure

First, participants signed a privacy consent form and were informed about the study procedure. Furthermore, they were informed that they could abort the study at any point in time, for example, due to MS symptoms. They then entered demographic data, including age, gender, handedness, vision impairments, and frequency of AR/VR usage on a five-point likert scale (*never* to *always*). Afterwards, they were introduced to the Varjo XR-3 and the Fitts' Law Task and could practice each interaction method until they felt comfortable using it [13]. Subsequently, the first measurement of the Misery Scale (MISC) [15] was collected, followed by participants putting on the HMD and performing the One-Dot Eye-Tracking Calibration as provided by Varjo Base. To ensure high accuracy and precision for Gaze&Pinch, participants were instructed to fixate the HMD comfortably but tightly to prevent the headset from moving and having a negative effect on eye-tracking. Subsequently the five-dot calibration of the Varjo XR-3 was performed for increased tracking precision when performing eye-tracking interactions. The calibration quality was then validated before the trial could start. We ensured high calibration quality for Gaze&Pinch by checking the calibration result obtained by VarjoAPI, as well as accuracy and precision measures obtained by using GazeMetrics [7]. We ensured that the accuracy would not exceed half the diameter of the Fitts' Law task targets. Participants performed each interaction method in a moving vehicle and in a standstill environment.

Then, participants started with the Fitts' Law Tasks. Every time participants finished the tasks, they filled out the questionnaires outlined in Section 3.5, followed by a semi-structured interview. The driving session was aborted if a MISC $\geq 6$ was reported [25, 53]. This process was then repeated for each interaction method. After participants completed each interaction method and movement combination, they concluded their participation by performing a final semi-structured interview. We ensured counterbalancing by applying a balanced latin square. The study took about 2.5 hours. Participation was voluntary.

## 3.4 Fitts' Law Task

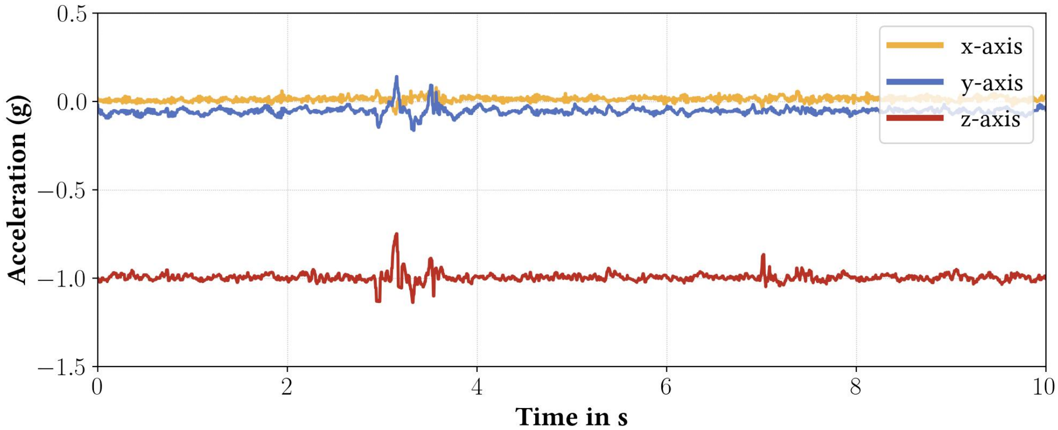
We employed a Fitts' Law Task to investigate the implications of standstill vs vehicle movement on point-and-select tasks with different interaction methods. To analyze user performance, we calculated throughput based on Batmaz and Stuerzlinger [11]. Here, the following formulation of effective throughput is used, with movement time representing the task completion time:

$$ID_e = \log_2 \left( \frac{A_e}{W_e} + 1 \right)$$

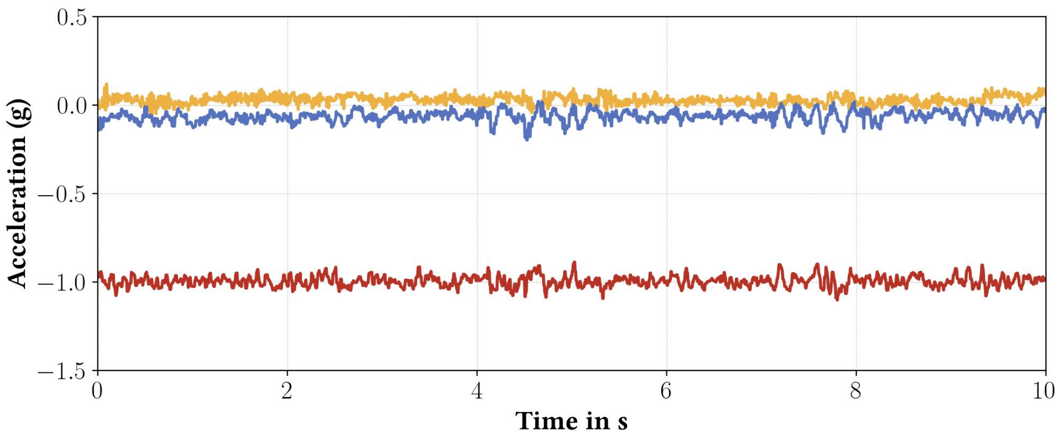
$$\text{Throughput} = \left( \frac{ID_e}{\text{MovementTime}} \right)$$

$A_e$ represents the actual traveled euclidean distance in three-dimensional space between the last and current selection. $W_e$ represents the effective target width and is calculated as $W_e = 4.133 \cdot SDx$. Similar to Batmaz and Stuerzlinger [11], we projected the standard deviation (SD) of the distance between the current selection point and the target center onto the task axis. Effective throughput was calculated for each repetition of seven targets.

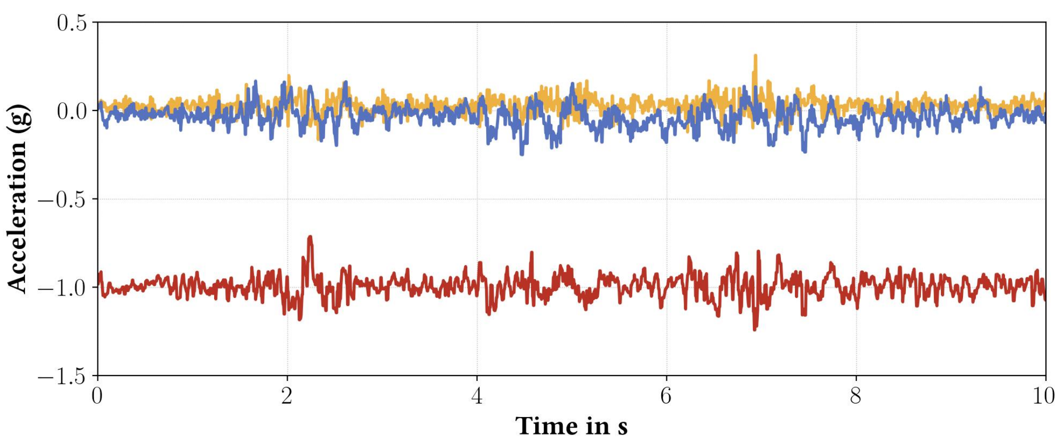
Based on Mixed Reality design guidelines by Microsoft [61], we placed the targets on a two-dimensional plane centered at 40cm in front of participants' heads, with a downwards offset of 20°. This ensured that the center of the interaction plane was positioned within the range of the resting gaze angle, providing a reduced risk of eye strain [69] while also providing an ergonomic area for head movements. The targets were arranged in a circular layout with an amplitude of 20° (i.e., the distance between the targets, 14.106cm at 40cm depth), requiring small head movements for selections performed with Gaze&Pinch [81]. The interaction plane on which the targets were positioned always faced the participant. Based on an internal evaluation (see Section 3.1) of the eye-tracker, we set the target size for the subsequent Fitts' Law Task to an angular size of 4.25° (2.9684cm width at 40cm depth), ensuring that tracking inaccuracy, which could occur to differing degrees based on the calibration quality and target position was accounted for. A green cursor of 1° size (0.69815cm at 40cm depth) was visible across all conditions except for Gaze&Pinch. We used these values across all input modalities to compare task-related metrics. Targets were displayed as white by default, with them being highlighted in red on hover. The next target to be selected was highlighted in blue, containing a smaller black circle in the middle to aid precision during Gaze&Pinch trials [86] (see Figure 3).




(a) SmoothRoad




(b) MixedRoad




(c) BumpyRoad

**Figure 4: Vehicle acceleration on the three road conditions: SmoothRoad, MixedRoad, and BumpyRoad. Recordings from P08 during Gaze&Pinch. The x-axis describes longitudinal, the y-axis lateral, and the z-axis vertical acceleration.**

**(a) SmoothRoad** **(b) MixedRoad** **(c) MixedRoad** **(d) BumpyRoad**

**Figure 5: Overview of road types investigated in our study, depicting variations in surface quality.**

The first target at the start of the block was highlighted in purple. All seven targets remained visible to the participants throughout the study. To provide additional feedback, correct and incorrect selections were accompanied by an individual acoustic signal. Selections that occurred in the area outside of targets also behaved this way. Participants were instructed to perform selections as fast and as precisely as possible. The task contained 44 repetitions, each involving the selection of seven targets, leading to 308 correct selection to be performed in total. For the Fitts' Law implementation, we used the open source implementation *3DFitts* by jlcouto[2]. We instructed participants not to rest their hands while using interaction methods which required pre-selection by hand movement. This was done due to the challenge of adjusting hand rests to accommodate for differences in body height and arm length in the vehicle. Because of the Gorilla-Arm effect [41], we introduced breaks across all interaction methods where participants could rest. Breaks took place after every eight repetitions and lasted for eight seconds. To ensure a correct analysis of the Fitts' Law Task, the first repetition after each break was excluded from the statistical analysis, with 266 correct selections remaining in the dataset. This ensured comparable starting positions for the cursor in context of the first target selection in each repetition.

## 3.5 Subjective Measures

*3.5.1 Trust and Perceived Safety.* We assessed the implications of the interaction methods on the participants' perceived safety and trust towards the AV. For trust, we employed the two sub-scales "Understanding/Predictability" and "Trust in Automation" of the Trust in Automation (TiA) questionnaire by Körber [51]. The subscale "Understanding/Predictability" assesses participants' ability to understand the reason behind performed maneuvers. Additionally, we measured subjective perceived safety using semantic differentials (-3 to +3) by Faas et al. [30].

*3.5.2 Usability and Workload.* We used the System Usability Scale (SUS) [16] to assess the subjective usability metrics. Furthermore, the NASA-TLX [39] was employed to assess the subjective workload exhibited by each method. Related scores were calculated based on the raw-TLX [39] (NASA-rTLX). For the total score, sub-scales were summed and divided by their count.

*3.5.3 Motion Sickness.* Due to the varying susceptibility of participants to MS symptoms, we continuously assessed MS during the study by administering the MISC questionnaire [15]. We terminated the study session if a value $\geq 6$ was reported [25, 53].

*3.5.4 Post-Condition and Post-Study Questionnaire.* Post-Condition and Post-Study semi-structured interviews were performed regarding user preferences, comparisons across conditions, challenges of use, possible improvements, and future usage of HMDs concerning potential benefits of their usage in vehicles (see Appendix A). We evaluated the gathered data by performing a thematic analysis. Quotes obtained in a language other than English were translated using DeepL.

*3.5.5 Fitts' Law Metrics.* For the entire Fitts' Law Task duration, we logged cursor movement and the position and rotation of participants' heads, hand palms, and index tips of the chosen handedness. Task-related metrics we assessed include correct and incorrect selections, the distance of the selection endpoint to the target center, movement time, throughput, effective width, and effective amplitude.

[2]jlcouto: 3DFitts. https://github.com/jlcouto/3DFitts, commit 7eef967; accessed 20.06.2024)

**Table 1: Classification of Road Types, Curve Types, and Maneuvers**

| Road Type | Curve Type | Maneuver |
|---|---|---|
| SmoothRoad | Short [Left/Right] Curve with Acceleration | Braking |
| MixedRoad | Long [Left/Right] Curve with Acceleration | Accelerating |
| BumpyRoad | Long [Left/Right] Curve with Steady Acceleration | |

## 3.6 Objective Measures

To analyze Fitts' Law-related data regarding the effects of vehicle motions, we collected vehicle acceleration, vibrations, and angular motion during driving sessions using a car-mounted LPMS-IG1P IMU, with a sampling rate of 250Hz and the x-axis values representing longitudinal accelerations[3]. Additionally, vehicle speed in km/h, movement of the acceleration and brake pedals, and the exact position along the course were recorded, with first preliminary labels being applied in real-time according to the current road conditions (e.g., BumpyRoad, SmoothRoad, MixedRoad) and curve categories (e.g., Short-Left Curve, Long-Left Curve with Steady Speed).

To assess the impact of vehicular motion on the body parts used for or related to performing interactions, we recorded the movement of the hands in space by utilizing the Ultraleap hand tracking, as well as the position and rotation of the participant's head. Furthermore, Eye-Tracking features (e.g., Focus Point, Pupillary Index) were recorded with a frequency of 100Hz using the standard Varjo filter during the whole study. For Gaze&Pinch this includes a post-calibration validation step based on GazeMetrics, measuring accuracy and precision later used to assess the related interactions. Reporting of these metrics is based on the RMS and accuracy formulas presented by B. Adhanom et al. [7].

While B. Adhanom et al. [7] states that a target arrangement similar to the system's native calibration procedure tends to result in better accuracy, we decided to use a circular layout consisting of nine targets, while using a radius of 20° at a depth of 0.4m to resemble the target visualization of the utilized Fitts' Law Task. Furthermore, based on [7], samples collected during the first 800ms are excluded with targets being visible for two seconds each.

## 3.7 Data Preparation

The raw data obtained within this study contained the parameters specified in Section 3.6 for *N*=24 participants, consisting of four interaction methods each performed during vehicle movement and standstill. As each data stream was recorded into a separate file due to differing sampling rates, raw data was first resampled to 200Hz, interpolated, and then synchronized based on UnixTime in milliseconds. This resulted in one file for each combination of factors.

Due to technical issues with the hand-tracking sensor, and based on the reports of participants, we recognized that unintentional selections (pinch gestures) were picked up by the hardware. By running an internal test to reproduce this issue, we found that selections with a duration of less than or equal to 70ms and a time interval from each other under 10ms to be erroneous and filtered them accordingly. Additionally, the technical issue also resulted in two selections being logged simultaneously. In such cases, the first recorded selection attempt was kept with the subsequent ones being removed. An exception to this filtering approach were correct selections - as they always led to a continuation of the Fitts' Law Task. This led to an average of 23.22 selections being filtered across factor combinations. A detailed analysis can be obtained in Section 4.5.

Afterwards, the data was automatically labeled. Vehicle movement was subdivided into the following labels, which extend over three categories taking place in parallel: Road Type, Curve Type, and Maneuver. See Table 1 for an overview regarding the assigned sub-labels. Road Types were assigned using the vehicle position along the pre-defined course, mapping each segment accordingly. Curves were categorized based on a feature combination of the vehicle speed in km/h, the z-axis values of the employed gyroscope, and the position along the course. The label Breaking was assigned based on values obtained from the vehicle's breaking pedal, while accelerations were categorized by using the vehicle speed.

[3]https://www.lp-research.com/9-axis-imu-with-gps-receiver-series/; Accessed 26.08.2024

# 4 User Study: Results

For the statistical analysis, we used RStudio (2024.09.1) and R (Version 4.4.2). All packages used were up-to-date as of December 2024. Analysis was performed by utilizing *rCode* by Colley [18]. Data was checked for normal distribution and homogeneity of variance for every statistical test. For non-normally distributed data, and if not stated differently, Aligned Rank Transform (ART) using the ARTool package [90] was applied. Post-hoc analysis was performed using Dunn's test with Holm correction [56].

## 4.1 Participants

24 participants aged between 23 and 60 years (*M*=33.0, *SD*=8.37, *Mdn*=31) participated in the study (3 female, 21 male, 0 non-binary). 5 participants were left- and 19 participants were right-handed. All participants except one were employees of an automotive company. Participants responses regarding the usage frequency of AR and VR devices ranged from *always (N=2)*, *often (N=6)*, *sometimes (N=4)*, *rarely (N=8)* to *never (N=4)*. None of the participants had to abort the study due to motion sickness.

Out of 24 participants, 20.8% (*N*=5) stated that they were nearsighted, while 25% (*N*=6) were nearsighted while also having astigmatism or were nearsighted and partially sighted on their left eye (4.2%, *N*=1). One participant stated to be farsighted (4.2%, *N*=1), and one was farsighted while having astigmatism (4.2%, *N*=1). 41.7% (*N*=10) had no vision problems. 54.2% (*N*=13) of participants reported regularly using prescription glasses, while 4.2% (*N*=1) reported using both, prescription glasses and contact lenses. 41.1% (*N*=10) do not use either. None of the participants stated to have a glaucoma or cataract.

## 4.2 Eye-Tracking Validation

Before using Gaze&Pinch, the accuracy and precision of the performed Eye-Tracking Calibration were validated using GazeMetrics [7]. The data was sampled at 100Hz, with Varjo Base filtering set to standard. Nine targets were displayed for 2s each, and samples within the initial 800ms were excluded. Targets were arranged in a circular layout, resembling the Fitts' Law Task. They were positioned at 40cm depth, featured an amplitude of 20° (14.106cm), and had an angular size of 5.0102° (3.5cm width). We obtained an average accuracy of 1.32° (*SD*=0.90, *Mdn*=1.10) and an RMS precision of 0.0848° (*SD*=0.180, *Mdn*=0.0339). For participant 26 (P26), One-Dot Calibration was performed in Gaze&Pinch Movement, as it yielded better calibration quality according to Varjo Base. Participant 12 did not use vision corrections while performing Gaze&Pinch during Standstill as opposed to the movement condition. For this participant, data is missing due to technical logging issues. Furthermore, we can differentiate between participants using prescription glasses. Table 17 contains the measurements per vision correction group.

## 4.3 Perceived Workload

In this section, we present results obtained from the NASA-rTLX questionnaire. The statistical analysis via ART found no significant effects on temporal demand or effort. However, the ART found a significant main effect of movement on the NASA-rTLX Total Score ($F(1, 23) = 9.52$, $p$=0.005). Total Score was significantly higher during movement (*M*=47.06, *SD*=18.82) than in standstill (*M*=42.48, *SD*=18.01). The ART found a significant interaction effect of interaction method × movement on NASA-rTLX Total Score ($F(3, 69) = 3.04$, $p$=0.035; see Figure 6). The Total Score of DirectTouch and Handray remain largely unaffected by movement, resulting in similar scores compared to standstill. For Gaze&Pinch and HeadGaze, the Total Score is higher during Movement than during standstill. The highest score is reached for HeadGaze during movement (see Table 2). The ART found a significant main effect of movement on mental demand ($F(1, 23) = 4.77$, $p$=0.039). Mental demand was significantly higher during movement (*M*=41.72, *SD*=27.80) than during standstill (*M*=36.88, *SD*=26.45).

The ART found a significant main effect of interaction method on physical demand ($F(3, 69) = 9.10$, $p$<0.001). Table 3 contains the results of the post-hoc test. Table 4 displays descriptive statistics.

**Table 2: NASA-rTLX Total Score (Mean and Standard Deviation for different interaction methods)**

| Interaction Method | Mean | Standard Deviation |
|---|---|---|
| DirectTouch Movement | 48.6 | 13.8 |
| DirectTouch Standstill | 47.9 | 16.6 |
| Gaze&Pinch Movement | 47.0 | 22.6 |
| Gaze&Pinch Standstill | 39.3 | 19.9 |
| Handray Movement | 42.2 | 20.4 |
| Handray Standstill | 42.1 | 17.6 |
| HeadGaze Movement | 50.3 | 17.6 |
| HeadGaze Standstill | 40.7 | 17.7 |

The ART found a significant main effect of movement on performance ($F(1, 23) = 31.13$, $p$<0.001). Performance was significantly lower with movement (*M*=43.39, *SD*=19.58) than during standstill (*M*=32.66, *SD*=18.11). As a high rating on this scale represents low self-perceived performance, participants reported performing better during standstill than during movement.

The ART found a significant main effect of movement on frustration ($F(1, 23) = 5.84$, $p$=0.024). Frustration was significantly higher with movement (*M*=43.65, *SD*=27.17) than during standstill (*M*=38.54, *SD*=25.76).

## 4.4 System Usability

The ART found a significant main effect of movement on SUS Score ($F(1, 23) = 14.18$, $p$=0.001). Usability was significantly lower with movement (*M*=72.01, *SD*=18.19) than during standstill (*M*=77.14, *SD*=16.83), see Figure 7.

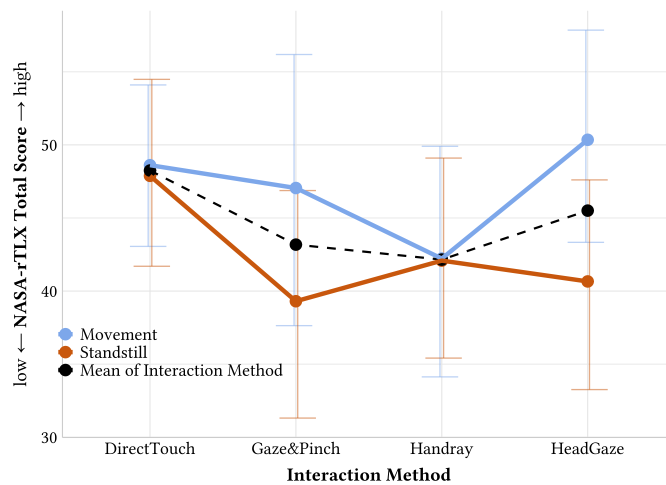



**Figure 6: Interaction effect on NASA-rTLX: Total Score**

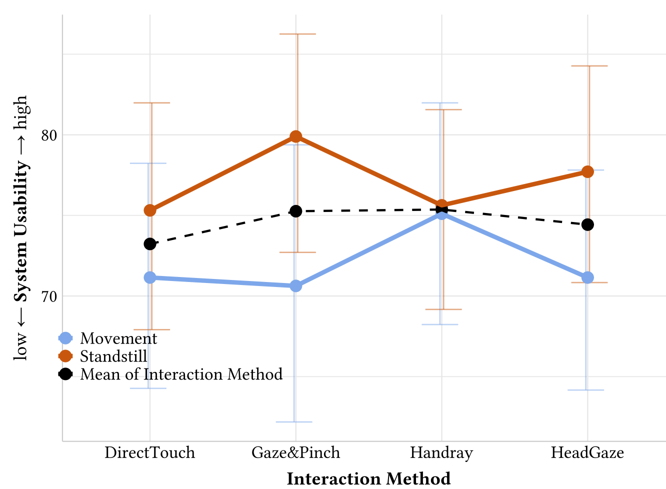



**Figure 7: Results of the System Usability Scale**

**Table 3: Post-hoc comparisons for independent variable interaction method and dependent variable *physical demand*. Positive Z-values mean that the first-named level is significantly higher than the second-named. For negative Z-values, the opposite is true.**

| Comparison | Z | p-adjusted |
|---|---|---|
| DirectTouch - Gaze&Pinch | 5.3139 | <0.001 |
| DirectTouch - Handray | 2.3585 | 0.0275 |
| DirectTouch - HeadGaze | 2.3244 | 0.0201 |
| Gaze&Pinch - Handray | -2.9555 | 0.0062 |
| Gaze&Pinch - HeadGaze | -2.9895 | 0.0070 |

**Table 4: NASA-rTLX: Physical Demand (Mean and Standard Deviation for different interaction methods)**

| Interaction Method | Mean | Standard Deviation |
|---|---|---|
| DirectTouch | 68.54 | 25.85 |
| Gaze&Pinch | 36.67 | 30.97 |
| Handray | 55.31 | 26.24 |
| HeadGaze | 55.52 | 25.08 |

## 4.5 Filtered Selection Count

To extend the filtering approach described in Section 3.7, we analyze the number of filtered selections to assess the influence of vehicle motion and compare the susceptibility across interaction methods.

The ART found a significant main effect of interaction method ($F(3, 69) = 11.40$, $p$<0.001), and of movement ($F(1, 23) = 64.85$, $p$<0.001) on filtered selections. The amount of filtered selections was significantly higher with movement ($M$=29.55, $SD$=36.99) than without ($M$=16.89, $SD$=27.15). Post-hoc analysis using Dunn's test revealed significant differences (see Table 5). The ART found a significant interaction effect of interaction method × movement on filtered selections ($F(3, 69) = 8.89$, $p$<0.001; see Figure 8). The largest amount of filtered selections during movement is visible for Gaze&Pinch, the lowest for DirectTouch. During standstill, the highest count is visible for Gaze&Pinch, the lowest for DirectTouch.

## 4.6 Fitts' Law

For the analysis of metrics related to the Fitts' Law Task, the data for throughput, movement time, and selection offset was filtered for outliers using Tukey's Inter Quartile Range (IQR). This defined outliers as data points which were either 1.5 times below the first or above the third quartile[4]. We exclude error rate from this approach, as it is derived from already pre-filtered selection data as explained in Section 3.7. Furthermore, as explained in Section 3.4, obtained data of the first repetition after a break were excluded from the statistical analysis.

*4.6.1 Throughput.* The ART found a significant main effect of interaction method on Fitts' Law throughput ($F(3, 69) = 4.23$, $p$=0.008). A post-hoc test found that throughput was significantly higher

[4]https://easystats.github.io/performance/reference/check_outliers.html; Accessed 04.12.2024

**Table 5: Post-hoc comparisons for independent variable interaction method and dependent variable filtered selection count. Positive Z-values mean that the first-named level is significantly higher than the second-named. For negative Z-values, the opposite is true.**

| Comparison | Z | p-adjusted |
|---|---|---|
| DirectTouch - Gaze&Pinch | -5.0636 | 0.0000 |
| DirectTouch - Handray | -2.7748 | 0.0138 |
| DirectTouch - HeadGaze | -2.5038 | 0.0184 |
| Gaze&Pinch - Handray | 2.2888 | 0.0221 |
| Gaze&Pinch - HeadGaze | 2.5598 | 0.0209 |

**Table 6: Fitts' Law: Throughput (Mean and Standard Deviation for different interaction methods)**

| Interaction Method | Mean | Standard Deviation |
|---|---|---|
| DirectTouch | 2.19 | 0.40 |
| Gaze&Pinch | 2.01 | 0.66 |
| Handray | 2.02 | 0.52 |
| HeadGaze | 1.93 | 0.47 |

for DirectTouch ($M$=2.19, $SD$=0.40) than for HeadGaze ($M$=1.93, $SD$=0.47, $p_{adj}$ = 0.0256, see Table 6). The ART found a significant main effect of movement on Fitts' Law throughput ($F(1, 23) = 122.10$, $p$<0.001). Throughput was significantly lower with movement ($M$=1.82, $SD$=0.45) than during standstill ($M$=2.25, $SD$=0.51; see Figure 9).

*4.6.2 Error Rate.* We calculated the error rate by dividing the number of incorrect selections by the total number of selections made and multiplied this score by 100 to obtain the percentage score. The ART found a significant main effect of interaction method

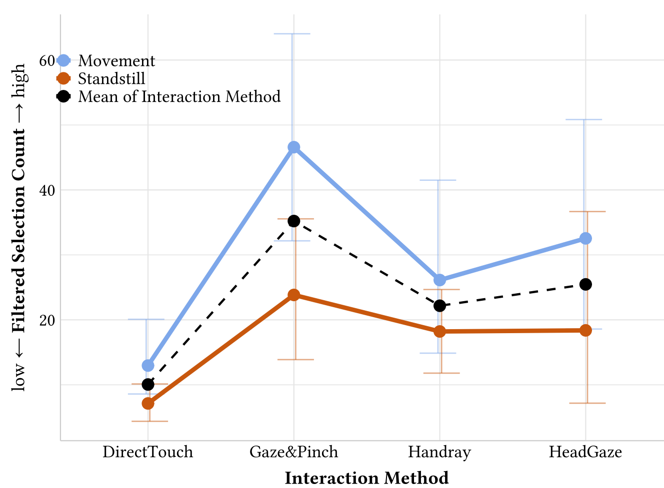



**Figure 8: Significant Interaction effect on Filtered Selection Count**

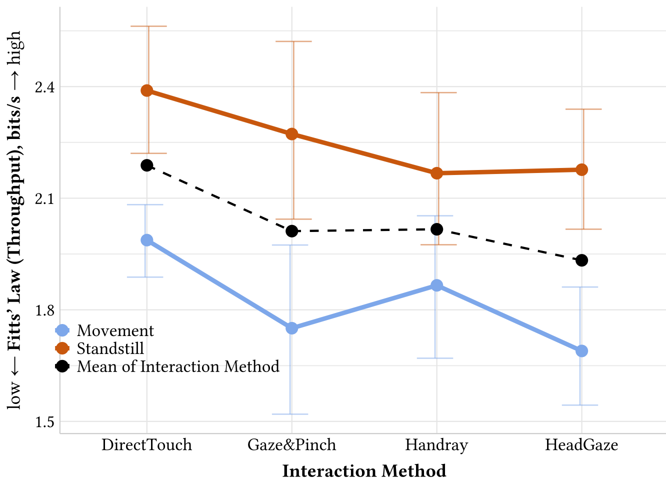



**Figure 9: Significant Main effects on Fitts' Law: Throughput**

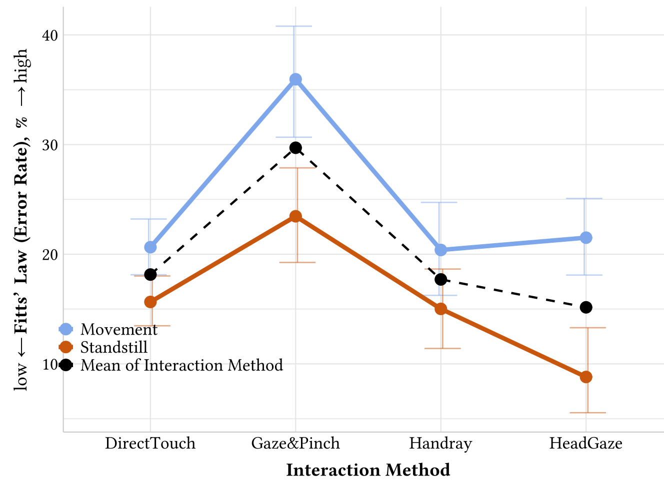



**Figure 10: Significant Interaction effect on Fitts' Law: Error Rate**

($F(3, 69) = 17.21$, $p$<0.001) and of movement ($F(1, 23) = 111.46$, $p$<0.001) on Fitts' Law error rate. The ART found a significant interaction effect of interaction method × movement on Fitts' Law error rate ($F(3, 69) = 15.72$, $p$<0.001). The error rate is higher during movement for every interaction method (see Figure 10). Compared to other interaction methods, Gaze&Pinch features the highest error rate in both movement conditions. HeadGaze has the lowest error rate across interaction methods in Standstill, while Handray has the lowest value in movement (see Table 7).

**Table 7: Fitts' Law: Error Rate (Mean and Standard Deviation for different interaction methods)**

| Interaction Method | Mean | Standard Deviation |
|---|---|---|
| DirectTouch Movement | 20.6 | 6.45 |
| DirectTouch Standstill | 15.6 | 5.91 |
| Gaze&Pinch Movement | 36.0 | 13.4 |
| Gaze&Pinch Standstill | 23.5 | 10.6 |
| Handray Movement | 20.4 | 11.0 |
| Handray Standstill | 15.0 | 9.23 |
| HeadGaze Movement | 21.5 | 9.07 |
| HeadGaze Standstill | 8.80 | 9.90 |

*4.6.3 Movement Time.* For analysis, we calculated the mean movement time per participant for each combination of factors. Movement time refers to the time required to perform one repetition consisting of selecting seven targets.

The ART found a significant main effect of interaction method on Fitts' mean movement time (s) ($F(3, 69) = 3.43$, $p$=0.022), with post-hoc analysis using Dunn's test not revealing significant differences. The ART found a significant main effect of movement on Fitts' mean movement time (s) ($F(1, 23) = 79.64$, $p$<0.001). Movement time was significantly higher with movement ($M$=9.38, $SD$=1.93) than without ($M$=7.97, $SD$=1.92; see Figure 12 and Table 8).

**Table 8: Fitts' Law: Movement Time in sec (Mean and Standard Deviation for different interaction methods)**

| Interaction Method | Mean | Standard Deviation |
|---|---|---|
| DirectTouch | 8.28 | 1.36 |
| Gaze&Pinch | 8.34 | 2.39 |
| Handray | 8.99 | 2.28 |
| HeadGaze | 9.08 | 1.93 |

*4.6.4 Selection Offset.* Selection offset describes the distance between the selection point and the center of the currently active target in millimeters. The ART found a significant main effect of interaction method ($F(3, 69) = 69.63$, $p$<0.001), and of movement ($F(1, 23) = 104.40$, $p$<0.001) on selection offset. The ART found a significant interaction effect of interaction method × movement on selection offset ($F(3, 69) = 24.61$, $p$<0.001; see Figure 11). The distance between selection and target center is larger during movement for all interaction methods, except for DirectTouch which contains comparable values. The difference between movement and standstill are largest for HeadGaze, followed by Handray and Gaze&Pinch.

## 4.7 Impact of Vehicle Motion

In this section, we analyze the task metrics selection offset and selection time of each combination of Interaction Method × Road Type × Curve Type. This approach allows us to identify which road characteristics affect which interaction method. The first repetition after a break was excluded from analysis (see Section 3.4). Due to missing sensor data, the recordings of the interaction method DirectTouch of Participant 11 were removed from subsequent analysis.

*4.7.1 Approach.* We fitted a linear mixed model (LMM) (estimated using REML and nloptwrap optimizer) to predict selection offset and selection time per movement. The model always included the participant as random effect (formula: ∼1 | participant). The model's

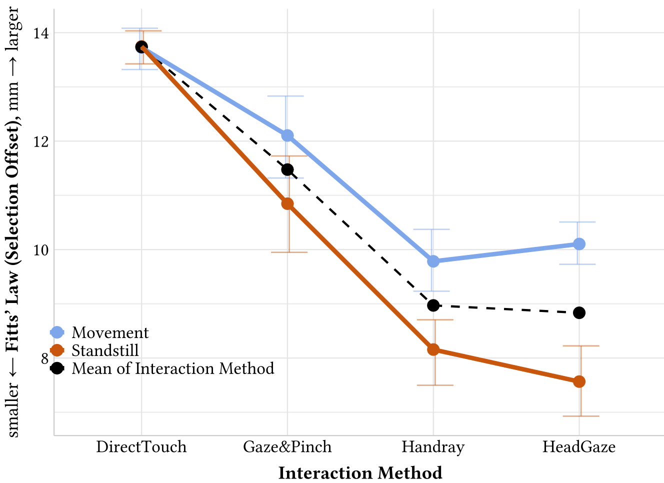



**Figure 11: Significant Interaction Effects on Selection Offset**

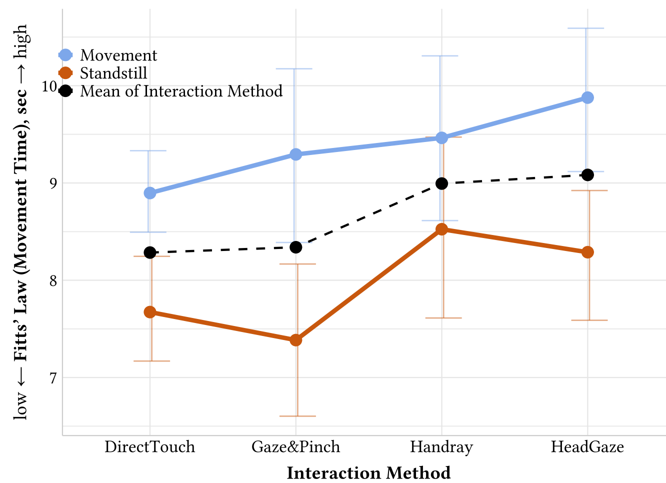



**Figure 12: Significant Main effect on Fitts' Law: Movement Time**

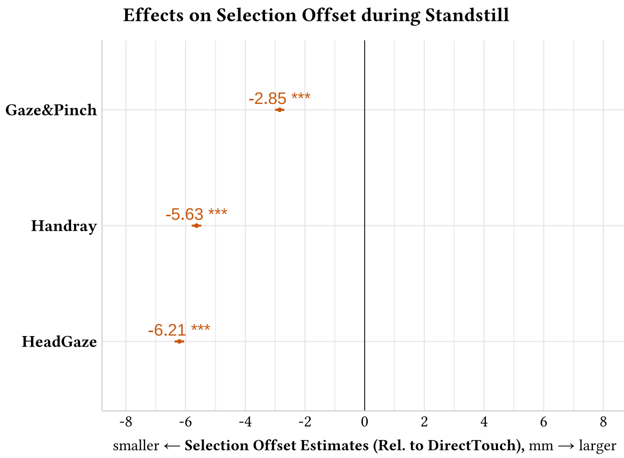
corresponded to interaction method = DirectTouch, and, for movement to Road Type = SmoothRoad and Curve Type = Straight road. For Standstill, we only evaluated the effect of interaction method as the course-related independent variables would not alter interaction during Standstill. The results obtained in the subsequent analysis are, therefore, always to be viewed relative to DirectTouch. Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald t-distribution approximation. As in Section 4.6, the data for selection offset and selection time were individually filtered for outliers using IQR. Furthermore, the data used contains correct and incorrect selections. In contrast to Section 4.6.3 selection time refers to the duration from the start of a target trial to its successful selection in seconds, allowing for increased granularity in the subsequent analysis.

*4.7.2 Selection Offset: Standstill.* The intercept is represented by DirectTouch and features an average selection offset of 13.83mm. The results show that the interaction methods Handray, HeadGaze and Gaze&Pinch significantly reduce the selection distance to the target center compared to DirectTouch (see Figure 13a, and Table 15). HeadGaze performed the best, followed by Handray and Gaze&Pinch. Furthermore, pairwise comparisons found significant differences as described in Table 9.

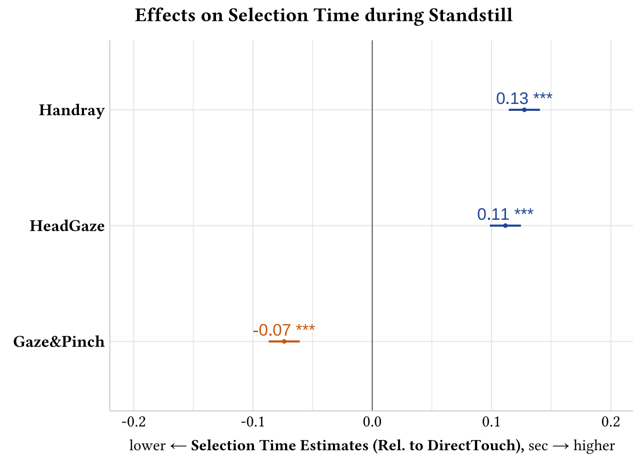
*4.7.3 Selection Offset: Movement.* We evaluate the effects on the selection offset size, representing the distance between the selection point and the target center, the effects of different conditions and their interactions with road and curve types are examined. The intercept is represented by DirectTouch and features an average selection offset of 13.43mm. During movement, and compared to DirectTouch, the interaction methods Gaze&Pinch, Handray, and HeadGaze significantly reduce the distance of selections to the target center (see Figure 14a, and Table 16). In comparison, these methods provide increased accuracy, with the lowest selection offset present for HeadGaze. Additionally, there is a three-way interaction effect for Handray and HeadGaze during Short-Left Curves with acceleration on BumpyRoad, showing significantly increased accuracy compared to DirectTouch. Decreased accuracy is found for several others. The road type MixedRoad and the curve type Long-Left-Curve with Acceleration increase the selection offset. BumpyRoad also reduced accuracy for HeadGaze, Handray, and Gaze&Pinch. The lowest accuracy is observed with the three-way interaction effect of Gaze&Pinch during a Short-Left Curve with accelerations performed on a MixedRoad. Here the selection offset is increased by 2.64mm on average compared to DirectTouch.

*4.7.4 Selection Time: Movement.* The intercept represented by DirectTouch features an average duration of 1.09s. Using Gaze&Pinch leads to significantly shorter selection times compared to DirectTouch. This improved performance also applies to the usage of the interaction method during BumpyRoad, and MixedRoad combined with varying curve types. Furthermore, all remaining interaction methods (Handray, HeadGaze) lead to significantly longer durations compared to DirectTouch. The only exception being HeadGaze, which had significantly shorter durations during Short-Right Curves with accelerations on BumpyRoad. Performing selection during Mixed- or BumpyRoad generally leads to a significantly increased time to perform selections. This also applies to multiple curve types (see Figure 14b, and Table 14). Three-way interactions found the highest selection duration for the interaction method Handray while being in a Short-Left Curve with acceleration on MixedRoad. Here, the duration increases on average by 0.31s.

*4.7.5 Selection Time: Standstill.* The intercept is represented by DirectTouch and features an average duration of 1.01s. Gaze&Pinch is the only interaction method that performed significantly better by featuring, on average, 0.07s lower selection durations than DirectTouch. Handray and HeadGaze performed significantly worse than DirectTouch, with Handray featuring the highest duration by taking, on average, 0.13s longer (see Figure 13b, and Table 13. Pairwise comparisons found significant differences as described in Table 10.

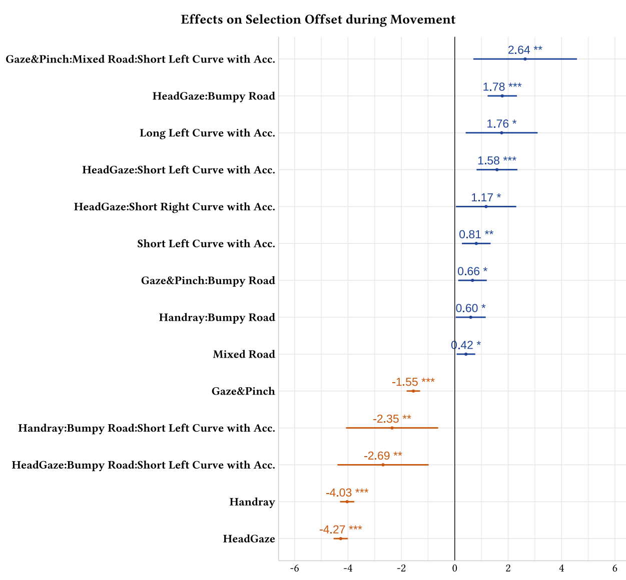



**(a) LMM for average selection offset between the selection location and the center of the current target in millimeters. The estimates describe the distance difference between Gaze&Pinch, Handray, HeadGaze relative to DirectTouch at standstill (selection offset = 13.83mm). Selections were estimated 6.21mm closer to the target center for HeadGaze compared to DirectTouch.**

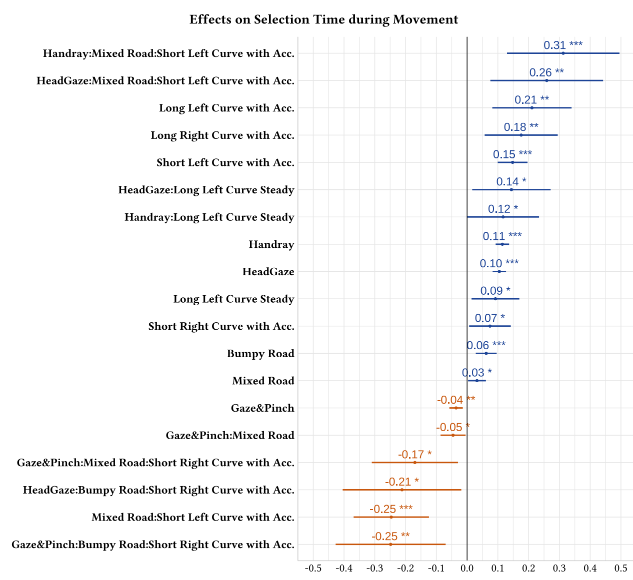



**(b) LMM for the average selection time from the start of a target trial to its successful selection in seconds. The estimates describe the time difference between Gaze&Pinch, Handray, HeadGaze relative to DirectTouch during standstill (selection time = 1.01s). Selections were performed 0.07s faster with Gaze&Pinch, while Handray increased this value by 0.13s compared to DirectTouch.**

**Figure 13: Significant results of LMM for selection offset and selection time during Standstill ('***' *p*< .001, '**' *p*< .01, '*' *p*< .05)**




**(a) LMM for the average selection offset between the selection location and the center of the current target in millimeters. The estimates describe the distance difference of road and curve types compared to DirectTouch on a straight SmoothRoad (selection offset = 13.43mm). Gaze&Pinch during a Short-Left Curve with Acceleration on a MixedRoad has the lowest precision with selection offset being 2.64mm larger compared to DirectTouch.**




**(b) LMM for the average selection time from the start of a target trial to its successful selection in seconds. The estimates describe the time difference of different road and curve types compared to DirectTouch on a straight SmoothRoad (selection time = 1.09s). Selections performed using Handray during a Short-Left Curve with Acceleration on a MixedRoad take the longest with selection times being 0.31s longer compared to DirectTouch.**

**Figure 14: Significant results of LMM for selection offset and selection time during Movement ('***' *p*< .001, '**' *p*< .01, '*' *p*< .05)**

**Table 9: Significant differences in selection offset during standstill. The estimates describe the distance differences between the listed interaction methods in millimeters.**

| Contrast | Estimate | SE | df | z-ratio | p-value |
|---|---|---|---|---|---|
| DirectTouch - Gaze&Pinch | 2.848 | 0.0791 | 29187 | 36.007 | <.0001 |
| DirectTouch - Handray | 5.633 | 0.0809 | 29183 | 69.602 | <.0001 |
| DirectTouch - HeadGaze | 6.207 | 0.0821 | 29183 | 75.640 | <.0001 |
| Gaze&Pinch - Handray | 2.785 | 0.0785 | 29176 | 35.465 | <.0001 |
| Gaze&Pinch - HeadGaze | 3.360 | 0.0797 | 29176 | 42.145 | <.0001 |
| Handray - HeadGaze | 0.574 | 0.0816 | 29175 | 7.037 | <.0001 |

**Table 10: Significant differences in selection time during standstill. The estimates describe the time differences between the listed interaction methods in seconds.**

| Contrast | Estimate | SE | df | t-ratio | p-value |
|---|---|---|---|---|---|
| DirectTouch - Gaze&Pinch | 0.0738 | 0.00667 | 24099 | 11.069 | <.0001 |
| DirectTouch - Handray | -0.1275 | 0.00666 | 24099 | -19.157 | <.0001 |
| DirectTouch - HeadGaze | -0.1116 | 0.00663 | 24099 | -16.847 | <.0001 |
| Gaze&Pinch - Handray | -0.2013 | 0.00658 | 24097 | -30.614 | <.0001 |
| Gaze&Pinch - HeadGaze | -0.1854 | 0.00655 | 24097 | -28.328 | <.0001 |
| Handray - HeadGaze | 0.0159 | 0.00653 | 24097 | 2.431 | 0.0715 |

*4.7.6 Trajectories.* To understand how the vehicle movement influenced interactions, we created exemplary 3d visualizations of dynamic situations impacting precision based on the results of Figure 14a). As expected, the movement condition presented a significant effect on user performance (F(1,23) = 57.44, p<0.001), with users being more accurate in estimating the position of the next target whenever the vehicle was at a standstill. The examples are based on participants whose number of erroneous selections matched the mean for each interaction method. The visualizations encompass cursor trajectories between targets within one Fitts' Law repetition and successful (green sphere) and unsuccessful (red sphere) selections (see Figure 5). The trajectories let us analyze the quality of the selection approaches and how external forces or environmental conditions could affect normal cursor movements. For example, a correct selection movement is characterized by smooth and fast approaches followed by short correction movements towards the target position (Ariza et al. [4]). In contrast, a BumpyRoad or a pronounced curve produces jerky or shifted trajectories. The trajectories of Gaze&Pinch were most affected by the vehicle movement, with the SmoothRoad being the least affected (Figure 15d). BumpyRoad condition presented the worst problems with numerous inaccuracies translated into the user retrying several times until finally confirming selections inside the target (Figure 15h). SharpLeftCurve presented fewer inaccuracies (e.g., targets 1 and 3) and shiftings (e.g., target 6, Figure 15l). In the case of DirectTouch, trajectories recorded in a SmoothRoad depicted normal approaches (Figure 15a), similar to BumpyRoad with additional inaccuracies close to target positions (Figure 15e). Finally, the vehicle movement during a SharpLeftCurve affected the trajectories in the shape of occasional incorrect selections followed by retrying. Regarding HeadGaze, on a SmoothRoad (Figure 15c), an increase in jerky directional changes within the trajectory can be identified for BumpyRoad, becoming noticeable in the run-up to the selection of the first target (Figure 15g). The forces exhibited during a SharpLeftCurve with acceleration cause trajectories to bend in the opposite direction of vehicle movement. In Figure 15k, this is visible for the movement between targets 2-6 and 6-3. On the contrary, Handray featured comparably consistent trajectories for all the road conditions (Figure 15b, Figure 15j), showing gaps to the targets, small enough to provide correct selections for BumpyRoad (Figure 15f).

## 4.8 Motion Sickness

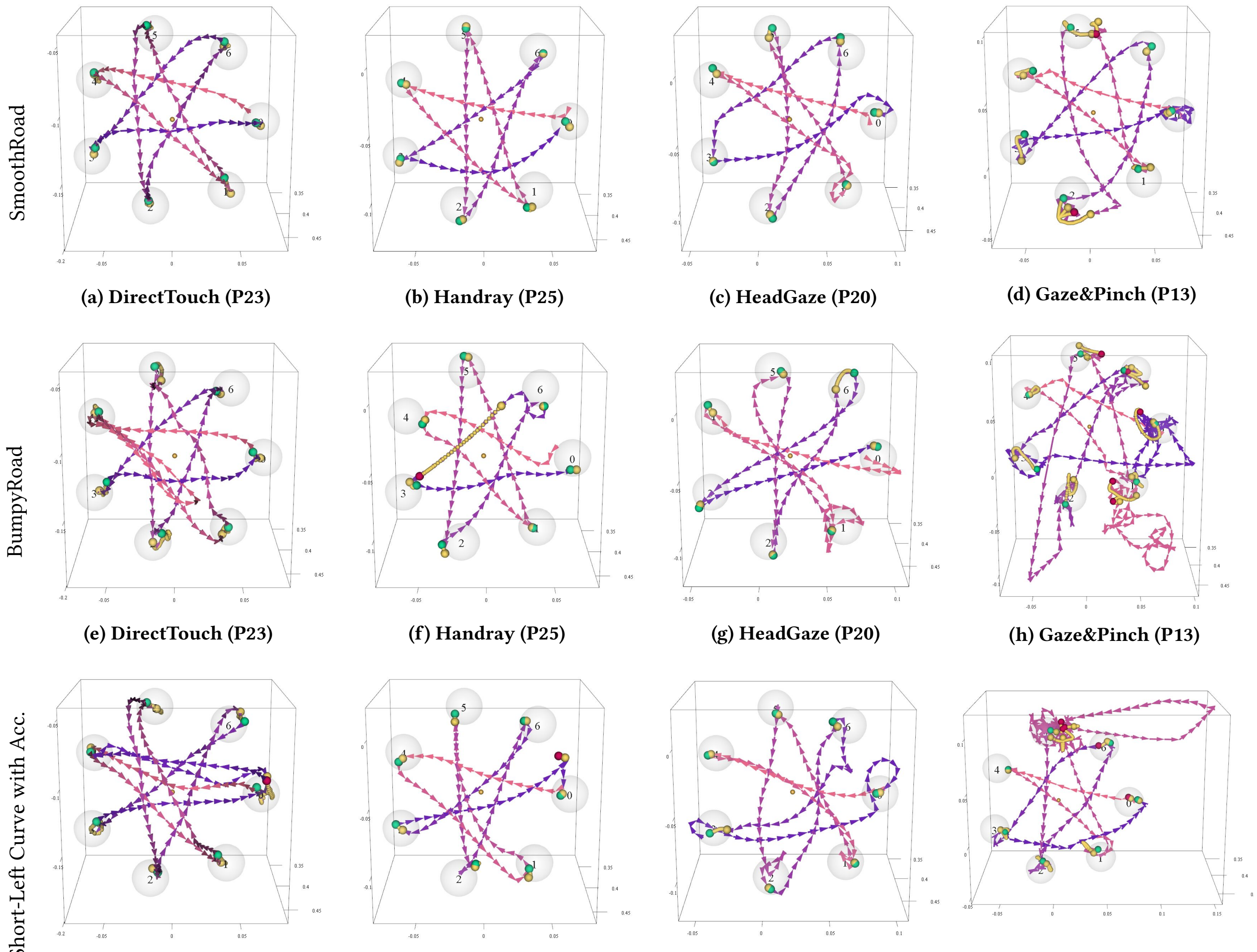
We analyzed the delta between measurements of the MISC performed before and after each condition. The ART found a significant main effect of movement on the difference in motion sickness before and after the task ($F(1, 23) = 5.75$, $p$=0.025). Motion sickness delta increased significantly more with movement ($M$=0.46, $SD$=0.89) than during standstill ($M$=0.03, $SD$=0.57).

## 4.9 Eye-Strain

The ART found a significant main effect of interaction method on Eye Strain ($F(3, 69) = 4.36$, $p$=0.007). A post-hoc test found that Eye-Strain was significantly lower for DirectTouch ($M$=2.04, $SD$=1.11) than for Gaze&Pinch ($M$=2.77, $SD$=1.32, $p_{\text{adj}} = 0.0150$).

## 4.10 Space Occupation

*4.10.1 Hand Palm.* For euclidean distance, the ART found a significant main effect of interaction method on hand palm ($F(3, 69) = 118.48$, $p$<0.001) and of movement on hand palm ($F(1, 23) = 71.24$, $p$<0.001). The ART found a significant interaction effect of interaction method × movement on the euclidean distance of hand palm ($F(3, 69) = 5.05$, $p$=0.003; see Figure 16). Values of movement condition are similar for DirectTouch but differ more for the other




(a) DirectTouch (P23) (b) Handray (P25) (c) HeadGaze (P20) (d) Gaze&Pinch (P13)

(e) DirectTouch (P23) (f) Handray (P25) (g) HeadGaze (P20) (h) Gaze&Pinch (P13)

(i) DirectTouch (P23) (j) Handray (P25) (k) HeadGaze (P20) (l) Gaze&Pinch (P13)

**Figure 15: Trajectories during user selections. The columns show the four interaction methods. The rows show road conditions. Green spheres represent successful selections, red spheres unsuccessful selections, and yellow spheres cursor movements between pinch-down and release. The sphere for pinch-down is larger, with smaller spheres representing cursor movements.**

interaction methods. For all interaction methods, euclidean distance is larger during movement than during standstill. DirectTouch is the interaction method which across movement conditions featured the highest values. For standstill, Gaze&Pinch features the lowest value, while for movement, Gaze&Pinch and HeadGaze have similarly low values (see Table 11).

*4.10.2 Head.* For the euclidean distance, the ART found a significant main effect of interaction method ($F(3, 69) = 39.58$, $p$<0.001), and of movement ($F(1, 23) = 459.08$, $p$<0.001) on head . The ART found a significant interaction effect of interaction method × movement on euclidean distance of the head ($F(3, 69) = 4.97$, $p$=0.004; see Figure 17). For Head, the values of each interaction method are higher with movement than with standstill. The highest value is represented by HeadGaze during both, movement and standstill. For standstill, the lowest value is assigned to Gaze&Pinch, while for movement the interaction methods DirectTouch, Gaze&Pinch, and Handray feature similar values (Table 12).

## 4.11 Perceived Trust and Safety

The ART found a significant main effect of movement on Trust in Automation ($F(1, 23) = 13.57$, $p$=0.001), on understanding ($F(1, 23) = 16.31$, $p$<0.001), and on perceived safety ($F(1, 23) = 8.71$, $p$=0.007). Trust ($M$=3.98, $SD$=0.80), understanding ($M$=3.65, $SD$=0.86), and perceived safety ($M$=1.60, $SD$=1.28) were significantly lower with movement than during standstill, where trust ($M$=4.35, $SD$=0.78), understanding ($M$=4.15, $SD$=0.68), and perceived safety ($M$=1.91, $SD$=1.06) were higher.

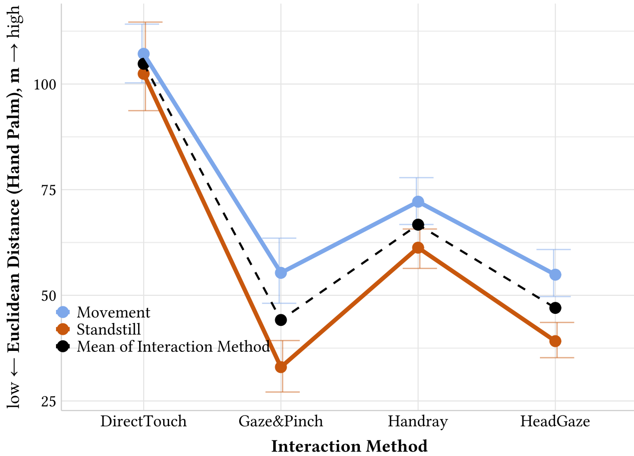



**Figure 16: Significant interaction effect on the euclidean distance covered by hand palm movements**

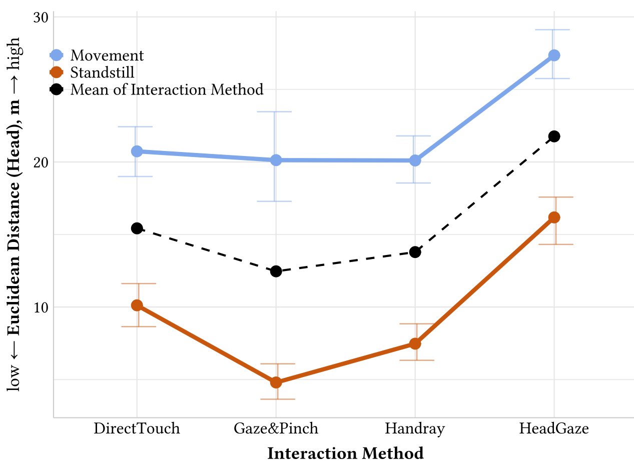



**Figure 17: Significant interaction effect on the euclidean distance covered by head movements**

## 4.12 Open User Feedback

We gathered qualitative feedback from participants to gain deeper insights into their experiences and perceptions. This encompassed two key areas: (1) the influence of road conditions on the interaction methods, (2) privacy concerns and considerations for public usage, and (3) general preferences between the different methods tested. We summarize the most frequently mentioned concerns and notable observations reported by participants.

*4.12.1 Influence of Road Conditions.* Participants highlighted that road conditions significantly impacted their interaction experience, affecting their preferences and effectiveness.

DirectTouch was highly appreciated for its simplicity, with many participants noting how intuitive it was and how it allowed them to stay aware of their surroundings. Several mentioned the value of understanding the external environment, such as why the vehicle slowed down. However, vehicle movements like bumps and curves caused challenges, leading to errors or misjudgments in interactions. Many participants also experienced physical strain, especially in the arms and shoulders, which was more pronounced during movement but still present at standstill.

Some users found the high level of precision required for effective interaction too demanding, particularly when the vehicle was stationary. While a few participants could compensate for vehicle movements during interactions, with P10 exemplary describing such situations as "(...) whenever there was bumps it was a little hard to get to the right point, but it was not too much and it was easily gone in a few seconds". Others consistently struggled with braking and acceleration, leading to errors. According to P03, breaking and curves led to underestimation, with the participant thinking that he "(...) was making mistake because I was doing the gesture for selection before I was touching the target.", adding furthermore that he "(...) was just going backwards before I was really touching the target". Additionally, technical issues with hand tracking were reported, with tracking loss near the target causing aborted or incorrect selections. The impact of vehicle movements, combined with physical strain and technical issues, suggests that improvements are needed to enhance the robustness and ergonomic comfort of this interaction method for vehicle-based applications.

The feedback on Gaze&Pinch highlighted its ease of use and high selection speed, with participants appreciating the method's

**Table 11: Euclidean Distance Hand Palm (Mean and Standard Deviation for different interaction methods)**

| Method | Mean | SD |
|---|---|---|
| DirectTouch Movement | 107.0 | 17.3 |
| DirectTouch Standstill | 102.0 | 27.9 |
| Gaze&Pinch Movement | 55.3 | 19.8 |
| Gaze&Pinch Standstill | 33.0 | 15.3 |
| Handray Movement | 72.2 | 13.9 |
| Handray Standstill | 61.3 | 12.2 |
| HeadGaze Movement | 54.9 | 14.4 |
| HeadGaze Standstill | 39.2 | 10.4 |

**Table 12: Euclidean Distance Head (Mean and Standard Deviation for different interaction methods)**

| Method | Mean | SD |
|---|---|---|
| DirectTouch Movement | 20.7 | 4.35 |
| DirectTouch Standstill | 10.1 | 3.75 |
| Gaze&Pinch Movement | 20.1 | 8.26 |
| Gaze&Pinch Standstill | 4.80 | 3.13 |
| Handray Movement | 20.1 | 4.07 |
| Handray Standstill | 7.47 | 3.25 |
| HeadGaze Movement | 27.4 | 4.46 |
| HeadGaze Standstill | 16.2 | 4.14 |

simplicity and precision. Many felt it allowed for quick, efficient interactions. However, vehicle motion presented significant challenges, especially during vibrations, which caused participants to lose focus and make incorrect selections.

Bumps were the most disruptive, followed by braking and curves. Many participants struggled to compensate for vehicle movements using only their gaze, feeling that it was much harder than hand-based interactions. This could be due to movement of the glasses leading to decreased tracking quality during sections with high movements. P11 "(...) found it incredibly difficult to select the points. The headset often wobbled. When I looked at a point, but the car wobbled at the same time and so did the glasses, I immediately lost focus on this point again and still pinched, so I had a wrong selection every time." A recurring issue was the coordination between pre-selecting a target with gaze and confirming the selection with the pinch gesture. Several participants found this disconnect between eye and hand actions led to frequent errors, as their gaze would shift too quickly before the pinch gesture was completed. Even during standstill, some participants reported eye-tracking inaccuracies, requiring them to adjust their gaze multiple times to ensure a target was properly highlighted. Overall, Gaze&Pinch shows potential for fast and precise interaction, but its effectiveness diminishes significantly with vehicle movement and coordination challenges between gaze and pinch actions.

The feedback for the Handray interaction method highlighted its ease of use and precision, with P20 highlighting its familiarity during standstill due to "(...) the fact that you don't just point, but make two separate movements, I think that reminds me of clicking with the mouse, so it feels very familiar to me". The biggest challenge during vehicle movement was handling the physical motion, followed by arm strain and issues with cursor smoothing. In the standstill condition, cursor smoothing was mentioned more often, with participants also reporting arm strain and feeling that the method was slow or physically demanding.

Some participants, however, felt that the difficulties were learnable, requiring small corrective movements to fine-tune the cursor's placement. Bumps were the most problematic vehicle maneuver, followed by curves and braking. In these situations, participants found it harder to compensate for the physical motion. Here, P13 noted that "Especially in curves and when it was bumpy, I was much less accurate. There were several mistakes in a row because I wasn't able to compensate". While bumps were hard to overcome, braking was seen as somewhat easier to correct for, as P13 stated that "When braking, I have the feeling that I can somehow compensate for this to some extent." Acceleration on the other hand was more difficult to predict or compensate for, as P20 described that "I don't think I have an instinctive feeling for how acceleration affects my movement. And that's why I can't compensate for this with the controls." Nevertheless, a few participants felt that curves, acceleration, and braking had little influence on their performance, and some mentioned that vehicle movement did not impact the interaction method at all. Overall, while participants found the method intuitive and precise, vehicle movements posed a notable challenge, especially during bumps.

Regarding the HeadGaze method, participants found the method to be precise, especially in the standstill condition, with some describing the interaction as comfortable in standstill, though no one mentioned this during movement. The biggest challenge during movement was the vehicle motion, which frequently disrupted participants' ability to maintain focus. Neck strain was a common complaint in both conditions, with the weight of the headset and required head movements being additional issues at a standstill. Cursor smoothing was also a problem, particularly in the standstill condition. Concerning vehicle maneuvers, bumps and curves were equally problematic, often disrupting the fixation of the cursor.

Regarding curves, P26 described the behavior as one where "(...) the fixation always flew out, corresponding to the curve" indicating that the forces exhibited during such maneuvers could not be compensated for. Adding to the influence of road bumps, P01 observed that "Especially when there was a bit more vertical travel, the cursor would sometimes hop across the entire screen", while humorously describing the method as awkward, likening it to "(...) trying to point at something with a wooden spoon taped to your forehead." Breaking and acceleration also presented challenges, with P01 suggesting that the system might work better on smoother roads, like highways, but not in urban environments. However, some participants felt that acceleration, braking, and bumps had little impact on their experience. Overall, while the HeadGaze method was seen as easy to use and effective during standstill conditions, vehicle movement, neck strain, and physical discomfort posed significant challenges, particularly during more dynamic driving situations like bumps and curves.

#### 4.12.2 *Privacy and Public Usage.*

Participants' perceptions of privacy and public usage of the four interaction methods varied significantly. Gaze&Pinch was considered the most comfortable and discreet interaction method when used around other passengers. It required minimal noticeable movements, with only the pinch gesture being perceptible to others. One participant emphasized that it was "(...) by far the least noticeable (...)" and they felt "(...) totally comfortable (...)" using it in public settings (P10).

DirectTouch was deemed highly noticeable to others due to the large, conspicuous arm movements involved. This made some participants uncomfortable, as they feared accidentally pointing at or invading the space of other passengers. One participant expressed concerns about others avoiding them during interactions. Several participants mentioned feeling particularly uncomfortable using this method around unknown passengers.

Handray was considered uncomfortable and very noticeable because of the large arm movements required. Participants felt this could invade others' personal space, noting that their movements might be distracting or disruptive. However, the movement was seen as natural by some, even if still very visible to those around them.

HeadGaze was viewed as the most noticeable interaction method since it required both head and hand movements, making it highly noticeable to others. Despite this, one participant indicated they wouldn't feel uncomfortable using it in front of others, particularly during vehicle motion, when the movement might be less apparent due to natural head motion caused by driving.

Figure 18 provides a comprehensive overview of participants' willingness to use specific interaction methods in a shared vehicle, based on their perceived comfort.

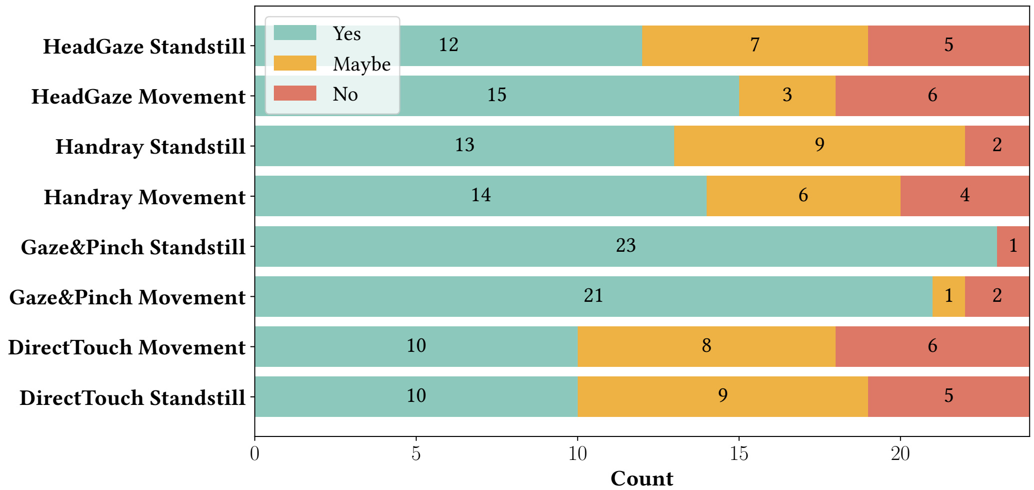



**Figure 18: Preference to use a specific interaction method in a shared vehicle, based on participants' perceived comfort**

*4.12.3 User Preferences.* During standstill, Gaze&Pinch was perceived as the fastest and most effective method, offering high precision and comfort for the selection task during standstill usage. While this method did not elicit physical demands similar to the other three, its requirement of eye movement for selections resulted in an increased eye-strain compared to its counterparts.

DirectTouch was rated as very strenuous compared to other methods, but allowed participants to achieve a high performance due to its ease of use. It furthermore enabled participants an increased perception of the outside environment. Regarding the implementation of targets, participants mentioned a too high requirement of input precision, as the cursor had to enter and leave the target within its bounds to achieve a successful selection. This should be accommodated for, for example, by only requiring and triggering a selection on touch-down instead of touch-up. HeadGaze was described as very slow during standstill, while Handray was described as causing arm strain due to its requirement of holding the hand in front of the headset to perform selections.

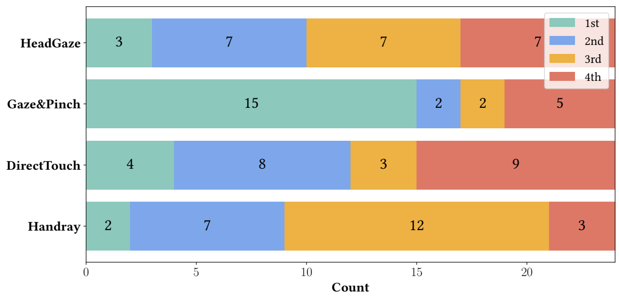
During vehicle motion, each of the presented interaction methods had its own set of limitations and challenges, influencing their individual ranking. The results convey increased user preference for Handray during movement as compared to standstill. Here, the amount of participants rating this interaction method as first preference increased fourfold, while no participants declared it to be their last preference anymore. Handray was described as a method requiring only low mental and physical workload while enabling target selection with high precision. The separation of pointing and selecting with the same extremity was furthermore highlighted as a positive aspect. This contrasts Gaze&Pinch, which popularity decreased during movement. While it received the largest count of votes as first preference ($N$=10) during movement, eight participants ranked it as their last preference, indicating that opinions are strongly divided regarding its usage. The method was rated positively due to the low physical workload exhibited. Furthermore, aspects like accuracy and ease of use were mentioned. However, some participants criticized the quality of eye-tracking, finding it imprecise and unstable during vehicle movements, requiring too much concentration. DirectTouch and HeadGaze on the other hand persist similar user rankings across movement and standstill, featuring a numerical tie regarding the amount of mentions for first and last preference during movement. While DirectTouch was perceived as intuitive and easy to use by participants, it required high physical effort, which could lead to arm strain. The method, therefore, was perceived as less comfortable than other methods. However, it enabled participants to interact with the system while simultaneously spectating the outside environment and therefore decoupled head movements from task input.

During movement, HeadGaze required a comparatively higher physical effort to compensate for vehicle motion than other methods. The method of steering the cursor by moving the head was perceived as strenuous and cumbersome by participants, with further physical effort being required by keeping the dominant hand in vision of the hand-tracking sensor as to perform the pinch gesture. However, some participants described the interaction method as comfortable but stressed the necessity of compensating vehicular motion to enable more precise input.

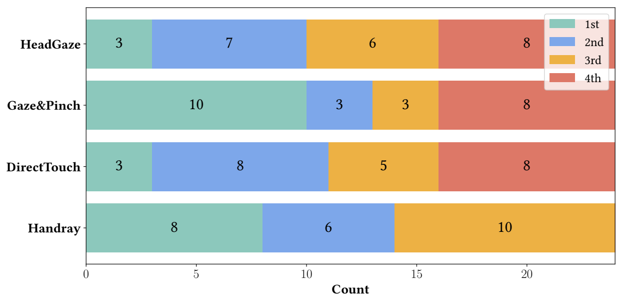
A complete overview regarding the most and least preferred interaction method across conditions is visualized in Figure 19a for standstill and in Figure 19b for movement. For improvements, participants suggested implementing a smoothing mechanism for the pointers of both, HeadGaze and DirectTouch, to improve input precision during vehicular movement.

## 5 Limitations

The headset, including the hand-tracking sensor and optical markers, weighed 1125g, which influenced the performance of interaction methods. Furthermore, external factors beyond our control, such as sunlight and varying ambient light conditions, may have influenced the tracking stability of the Ultraleap Leap Motion 2




**(a) Ranking of interaction methods for Standstill Usage**




**(b) Ranking of interaction methods for Movement Usage**

**Figure 19: Ranking of interaction methods**

controller. The eye-tracking system proved sensitive to vehicle vibrations, particularly pronounced on BumpyRoad. These vibrations may have caused relative movement between the HMD and participants' heads, reducing the quality of data collected during vehicle motion. As the shifting of HMDs is not a new observation, we expect this issue to occur for anyone using such eye-tracking systems in a moving context. This highlights the need for more robust tracking systems to compensate for such external disturbances. As the study was performed under real-life conditions in a traffic-calmed but public environment, external factors such as traffic influenced driving behavior. In rare cases, for example, there were longer braking times at junctions to give way. Finally, our participant pool was of moderate size, and results might not be generalizable as the group consisted of individuals employed by an automotive company, potentially resulting in an increased affinity towards AR and VR HMDs.

# 6 Discussion

We conducted a field study with 24 participants to investigate the impact of vehicular motion on task performance, perceived workload, usability, perceived safety, and trust in automation using an HMD and a Fitts' Law Task. Selections were performed using Gaze&Pinch, DirectTouch, Handray, and HeadGaze during standstill and movement. Data was categorized into combinations of Interaction Method × Road Type × Curve Type, revealing effects on selection offsets and duration. User preferences and methods were assessed, with suggestions for future improvements.

## 6.1 Impact on Usability, Perceived Workload and Task Performance — RQ1

We found a significant impact of movement, leading to increased perceived workload (see Section 4.3) and reduced task performance (see Section 4.6), causing lower usability scores (see Section 4.4). According to Bangor et al. [10], our interaction methods featured *good* (> 71.4) usability scores during standstill. However, usability scores decreased significantly during movement, resulting in the descriptive label *ok* (> 50.9), except for Handray, whose usability score remained largely unaffected by vehicle movement. Since Handray featured the lowest error rate (see Figure 10) and the best precision values (see Figure 11) during movement, we assume cursor smoothing to be an important factor in maintaining usability scores. Although participants referred to smoothing as cause for perceivable slow interactions (see Figure 12 and Section 4.12.1), its usage resulted in consistent trajectories (see Figure 15) during otherwise highly perturbed movements, thus allowing precise and intuitive selections (see Section 4.12.1).

Schramm et al. [79] performed a similar study, but their implementation of HeadGaze and Eye-Gaze required a hardware button to confirm the selection rather than a pinch gesture. Compared to Schramm et al. [79], all interaction methods but Handray received lower usability scores. We assume this to be due to our task requiring more selections in a short time, which led to increased time pressure. In the study by Schramm et al. [79] participants had five seconds per target, and breaks between the 70 horizontally arranged targets to be selected. In contrast, our participants had to perform 308 correct selections as quickly and accurately as possible while targets were arranged circularly, requiring diagonal movements. In addition, our course featured mixed and bumpy road segments, increasing complexity. Similar to usability scores, the impact of vehicle movement on total workload score is more pronounced for HeadGaze and Gaze&Pinch, while values for DirectTouch and Handray only increase marginally (see Table 2).

Based on findings by Mayer et al. [57], Colley et al. [22] and Ahmad et al. [3] we expected a stronger impact of external forces on precision and physical demand of the free hand pointing methods DirectTouch and Handray. However, contrary to Colley et al. [22], DirectTouch showed no relation between high physical demand and decreased accuracy during movement (see Figure 11), despite requiring a stretched arm to reach targets. Nonetheless, this requirement elicited significantly higher physical demand than all other interaction methods, thus causing Gorilla Arm fatigue [41]. The comparably small impact of movement also becomes apparent in the exemplified trajectories (see Figure 15), containing only occasional incorrect selections during BumpyRoad or Short-Left Curve with Acceleration. Compared to DirectTouch, Handray exhibited significantly less physical demand, required less arm movement (see Section 4.10.1), and allowed participants to keep the arm closer to their body, increasing stability. This minimized the Gorilla Arm effect in comparison to DirectTouch [41, 62]. Interestingly, Handray had the second largest decrease in precision during movement. We assume this is due to difficulties in predicting how acceleration affects hand movements and the smoothing behavior necessitating corrective movements for accurate selections (see Section 4.12.1). For HeadGaze, participants negatively highlighted the requirement for constant head movement, which caused neck strain. Here, HeadGaze featured the highest value for traversed distance in both movement conditions, with movement featuring an increased value (see Figure 17). Gaze&Pinch during movement elicited a higher total workload than during standstill. In line with Colley et al. [22], Gaze&Pinch requires significantly less physical demand than all other interaction methods while causing increased eye strain. In line with Blattgerste et al. [14], there was less head movement required for Gaze&Pinch than for HeadGaze. Furthermore, interesting to note is that Gaze&Pinch requires the lowest head movement across all conditions during standstill, while also containing the largest increase in head movement from standstill to movement across interaction methods. This could be linked to issues with the eye-tracking system (see Section 6.3), causing participants to more often try and support the eye-gaze selections with additional head movements [81]. Regarding Fitts' Law throughput, our results for Handray and Gaze&Pinch during standstill are similar to Wagner et al. [86], but our interaction methods achieved higher throughput. Movement features significantly reduced throughput across interaction methods, with DirectTouch offering the highest values, followed by Handray, Gaze&Pinch, and HeadGaze (see Figure 9). Handray featured higher throughput during movement (1.87 bits/s) than the overall equivalent of Wagner et al. [86] during standstill (1.39 bits/s). Furthermore, movement led to increased erroneous selections for all interaction methods. In line with Colley et al. [22], Gaze&Pinch featured the highest error rate across movement conditions. Although our implementation performed better than the one of Colley et al. [22], it did not outperform HeadGaze and thus opposes findings by Blattgerste et al. [14]. Similar to our results, Schramm et al. [79] found that HeadGaze resulted in low error rates. However, they identified the highest error rate for their implementation of Handray, while our implementation featured the lowest error rate during movement. An influencing factor for their increased error rate was the arrangement of targets in Schramm et al. [79], as they mention right-handed participants hitting their hand against the vehicle door while trying to perform selections, resulting in failed interactions.

## 6.2 Variance Across Vehicle Movements — RQ2

Interaction methods generally performed better during standstill than during movement (e.g., see Figure 9 and Figure 11), which was to be expected as external forces were not present [22]. While Ahmad et al. [2, 3] investigated the influence of varying road conditions, and Mayer et al. [57] focused on simulated road bumps, we extended these approaches by performing a field study in standstill and in movement on three road conditions (SmoothRoad, MixedRoad, BumpyRoad), additionally introducing three curve types (see Table 1) which were driven with and without increasing acceleration. Our findings align with previous works, as movement significantly impacted factors like selection offset [3, 22, 57], and error rate [2, 3, 22]. While we did not investigate individual road bumps as performed by Mayer et al. [57], our findings are in line with Ahmad et al. [3], Mayer et al. [57] as they found selection offset to increase as a result of road bumps. BumpyRoad caused either multiple retries per selection (Gaze&Pinch, Figure 15h), inaccuracies nearby targets (DirectTouch, Figure 15e), jerky directional changes in combination with nearly overshooting (HeadGaze, Figure 15g), or could lead to undershooting (Handray, Figure 15g). Effects were most strongly pronounced for HeadGaze, followed by Gaze&Pinch, and Handray (Figure 14). We assume that BumpyRoad led to decreased eye-tracking quality for Gaze&Pinch, as participants reported losing focus as the HMD shifted on their heads during vibrations (see Section 4.12.1). This occurred even though we instructed participants to tighten the headset firmly but comfortably on their head, indicating two aspects: 1) We assume that the HMD weight was too large to keep it in a stable position during the influence of road bumps, 2) as there is a calibration procedure for a fixed eye-position, employed eye-tracking algorithms might not be optimized for sudden changes in eye-position in relation to the tracking cameras. We further assume that the HMD weight significantly contributed to HeadGaze being the most affected interaction method, making it difficult for participants to compensate the forces exhibited on their neck muscles, leading to neck strain (see Section 4.12.1). Even though participants could stabilize their hand with the body while using Handray, they reported the inability to compensate for sudden movements like road bumps (see Section 4.12.1), causing decreased accuracy. The precision of DirectTouch was only significantly influenced by MixedRoad, aligning with previous findings that it is only slightly impacted by movement (see Section 6.1). Adding to previous works [2, 3, 22, 57], we found significant effects for combinations of Short-Curves with Acceleration on BumpyRoad (Handray, HeadGaze), Short-Curves with Accelerations on MixedRoad (Gaze&Pinch), Short-Curves with Acceleration (DirectTouch, HeadGaze), and Long-Left-Curves with Acceleration (DirectTouch) on precision. Since Short-Curves with Acceleration are the most occurring curve type, we assume that rapid and brief lateral accelerations are responsible for reduced precision. This can be observed in Figure 15, as only the paths between a few targets are affected per curve.

While Ahmad et al. [3] found increasing variability in task completion times with the amount of noise exhibited by the road profile, we identified this only for curve types. Additionally, all curve types, except for Long-Right-Curve Steady, resulted in significantly increased selection times. Long-Curves with Steady Acceleration primarily affected HeadGaze, Handray, and DirectTouch, with the latter being the only one affected by Long-Curves with Acceleration. Short-Curves with Acceleration impact DirectTouch, and in combination with MixedRoad also HeadGaze and Handray. We expect that selection times are extended by the time required to compensate exhibited lateral accelerations, something participants struggled with (see Section 4.12.1). We found rather unexpected results in improved selection times for Gaze&Pinch and DirectTouch on MixedRoad, and for HeadGaze and Gaze&Pinch on BumpyRoad, both during Short-Curves with Acceleration. This behavior could have emerged from participants trying to quickly correct previous selection errors. Furthermore, while Mayer et al. [57] found no significant effects of bumps on selection times, we could identify significant influences for DirectTouch and the aforementioned combinations of curve types with Mixed- and BumpyRoad.

Overall, significant findings in Figure 14 showed that primarily lateral accelerations influence selection times, while precision was impacted by a more balanced mixture of lateral and vertical accelerations.

## 6.3 Improving Interaction Methods — RQ3

While we employed a state-of-the-art sensor (Ultraleap Leap Motion 2) mounted with a 15° downward angle to increase hand visibility, technical issues with hand tracking were reported for all interaction methods, especially for DirectTouch and Gaze&Pinch. Direct sunlight and infrared light emitted by the utilized Optitrack V120:DUO camera can influence the tracking stability of the Ultraleap Leap Motion 2 [84]. This could scarcely result in tracking loss near the targets during DirectTouch, leading to erroneous cursor placement and causing incorrect selections or prohibiting selections.

The system registered unintentional pinch gestures, resulting in multiple selections in a very short interval (see Section 3.7). This can be due to issues with the *Ultraleap Leap Motion Controller 2* and the threshold defined within the Unity XRI. The gesture requires participants to maintain a pre-defined distance between the thumb and index tip, then bring them together and move them apart to perform the pinch gesture. We suspect that participants could not consistently maintain this distance for the study. As a result, small finger movements could have been sufficient to trigger a selection unconsciously. Similar behavior was also identified by Pfeuffer et al. [70], where participants brought their hands into a comfortable position, resulting in unintentional selections. Furthermore, the probability of such erroneous selections was increased by vehicle motion (see Section 4.5 and Section 4.6.2), presumably as it affects the movement of the body and limbs. Another possible reason for a failed pinch gesture could be that the fingers were not moved far enough from each other after being brought together successfully [62]. Furthermore, while this was not mentioned by participants, they had to keep their hands in a position visible to the sensor, a technical limitation that could also have led to unregistered selections during the study. Until such challenges are resolved, a hardware button could provide a viable alternative, offering similar performance while reducing frustration and recognition errors [62].

Regarding Gaze&Pinch, a recurring theme (see Section 4.12.1) was the coordination between pre-selecting a target with eye-gaze and performing the pinch gesture. To mitigate this issue, a short delay or snapping mechanism could be introduced to ensure the target stays active longer and allows the user to react in time. Pfeuffer et al. [69] suggest using the last fixation and stabilizing the gaze for 200 - 300ms.

While participants reported the cursor smoothing of Handray to be slow and thus challenging to perform selections with (see Section 4.12.1), largely unaffected trajectories (see Figure 15) along with highest precision during movement (see Section 4.6.4) indicate that it helped mitigate the influence of accelerations. As Handray was further characterized as easy to use and precise, we suggest keeping the initial concept of the cursor smoothing. However, the degree of smoothing could be dynamically adjusted based on measured accelerations. For example, a low smoothing value could be employed during SmoothRoad, possibly resulting in reduced selection durations and increased throughput. When erratic movements occur (e.g., road bumps), the smoothing value could be increased to stabilize cursor positions. Such behavior could also be adapted for other interaction methods, as suggested by participants regarding HeadGaze and DirectTouch (see Section 4.12.1).

## 6.4 Practical Implications and Guidelines

*6.4.1 Which interaction method should I implement?* Based on our findings, we recommend Handray for selection tasks during movement. While it could lead to arm strain, it featured the lowest error rate and highest precision and was preferred by participants. Handray removes distance constraints regarding positioning digital content as it utilizes a raycast for pointing. However, it might be unsuitable for public transport, as it could involve invading others' personal space. We also highlight Gaze&Pinch as a possible alternative in the future because participants rated it as their second preference. This was interesting as it featured the highest error rate but compelled participants through low physical demand and simplicity when it worked well. It is the most accepted interaction method when other passengers are present. For its usage, issues with eye-tracking in highly perturbed situations must first be resolved.

*6.4.2 Movement Considerations for Future Research.* Our findings highlight the importance of including curves in experimental designs due to their impact on selection times and precision. Short-Curves with Acceleration were the most common type, significantly impacting precision and duration values (see Section 6.2). We also recommend performing interactions during a standstill, or at least on a straight SmoothRoad, to assess the impact of movement precisely.

*6.4.3 Motion Fidelity Considerations.* Interaction methods performed significantly worse during movement than standstill, highlighting the importance of motion. Previous studies investigated interactions during motion using 1-DoF [22] and 6-DoF [57] simulators, or used a real vehicle [2, 3, 79]. While we found effects on error rate and selection offset, which were also found for simulator-based studies [22, 57], significant impact of individual road bumps on selection times obtained in a 6-DoF simulator did not align with our results for BumpyRoad [57]. Furthermore, no study investigated lateral acceleration in curves. Thus, we can not estimate how suitable motion platforms are.

Nonetheless, previous studies showed that motion simulators can provide comparable results, enabling a lower entry barrier. We argue that introducing any movement is better than including none, as external factors are hard to predict, with results hardly being transferrable from standstill to movement.

As it was difficult to compare our work to the few previous studies, each with their implementation of interaction methods, we make our configuration for the interaction methods available, hoping to improve reproducibility.

## 7 Conclusion and Future Work

We conducted a field study with 24 participants on a course with varying road types (SmoothRoad, BumpyRoad, MixedRoad) and curve types (Short-Curves with increasing acceleration, Long-Curves with increasing and steady acceleration). We investigated the impact of movement on DirectTouch, Handray, Gaze&Pinch, and HeadGaze using an HMD and a Fitts' Law Task. During the study, all interactions and movements of participants were recorded along with vehicle movements, and automatically labeled into road and curve types. We used this dataset to precisely analyze which type of movement significantly affected the accuracy and selection time of each interaction method. Interaction methods generally performed worse during movement, compared to standstill. We furthermore identified that each interaction method was affected by movement in a different way. For example, the NASA-rTLX total workload of HeadGaze and Gaze&Pinch were affected stronger by movement than DirectTouch and Handray. Furthermore task performance, accuracy, and selection time were negatively influenced. Based on our findings we presented practical implications and guidelines, among which we recommend the usage of Handray for selection tasks during movement.

We plan on further evaluating the influence of movement on pointing trajectories, focusing on occurrences of over- and under-shooting. As we aim to reduce erroneous selections, we plan to evaluate whether prediction approaches similar to Ahmad et al. [2] and Mayer et al. [57] can be used in conjunction with our task and interaction methods.

## Open Science

Upon acceptance, the source code and the analysis will be released here.

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# A Semi-Structured Interview

## A.1 Post Condition Interview

The following questions were asked every time a participant finished an input method:

- Which challenges did you notice during task execution?
- What did you notice positively, and what negatively?
- Could you imagine using this method in the future, and for which use-case?
- What did you perceive of the outside environment?
- How noticeable did you feel your interaction with the system was to other passengers?
- How comfortable would you feel using this interaction method in a vehicle with other passengers?
- *After a condition has been performed in both movement and still-stand:*
  - By comparing the usage of the input method between driving and stillstand, which differences did you notice?
- *If input method was performed in a moving vehicle:*
  - Did you notice any vehicle movements that influenced the interaction with the system?

## A.2 Final Interview

The following questions were asked after participants finished all conditions:

- Please rank the utilized input methods once for usage in a moving vehicle, and once for usage in a standing vehicle.
- If you could make any changes to any of the provided input methods, what would you modify and why?
- While driving, were there any situations where you felt a specific input method was less suitable or inefficient than another, and why?

# B Ultraleap Hyperion Configuration

Hints provided to the Hinting API. In Order:

- high_background_illumination
- ultra_performance_mode
- microgestures
- high_hand_fidelity
- user_input

## C LMM Estimates

**Table 13: Significant estimates of the LMM for Selection Time during Standstill. The intercept is represented by DirectTouch. The estimates describe the time differences between the listed terms and the intercept in seconds.**

| Term | Estimate | SE | t | p-Value |
|---|---|---|---|---|
| (Intercept) | 1.008 | 0.038 | 26.197 | < .001 |
| Gaze&Pinch | -0.074 | 0.007 | -11.069 | < .001 |
| Handray | 0.128 | 0.007 | 19.157 | < .001 |
| HeadGaze | 0.112 | 0.007 | 16.847 | < .001 |

**Table 14: Significant estimates of the LMM for Selection Time during Movement. The intercept is represented by DirectTouch with road type SmoothRoad, and curve type Straight Road. The estimates describe the time differences between the listed terms and the intercept in seconds.**

| Term | Estimate | SE | t | p-Value |
|---|---|---|---|---|
| (Intercept) | 1.087 | 0.033 | 33.253 | < .001 |
| Gaze&Pinch | -0.036 | 0.011 | -3.215 | 0.001 |
| Handray | 0.115 | 0.011 | 10.258 | < .001 |
| HeadGaze | 0.105 | 0.011 | 9.409 | < .001 |
| Bumpy Road | 0.062 | 0.017 | 3.587 | < .001 |
| Mixed Road | 0.032 | 0.015 | 2.175 | 0.030 |
| Long Left Curve with Acc. | 0.211 | 0.066 | 3.207 | 0.001 |
| Long Left Curve Steady | 0.092 | 0.040 | 2.325 | 0.020 |
| Long Right Curve with Acc. | 0.176 | 0.061 | 2.902 | 0.004 |
| Short Left Curve with Acc. | 0.148 | 0.025 | 5.985 | < .001 |
| Short Right Curve with Acc. | 0.074 | 0.035 | 2.153 | 0.031 |
| Gaze&Pinch:Mixed Road | -0.046 | 0.021 | -2.199 | 0.028 |
| Handray:Long Left Curve Steady | 0.117 | 0.060 | 1.966 | 0.049 |
| HeadGaze:Long Left Curve Steady | 0.144 | 0.065 | 2.216 | 0.027 |
| Mixed Road:Short Left Curve with Acc. | -0.246 | 0.062 | -3.945 | < .001 |
| Handray:Mixed Road:Short Left Curve with Acc. | 0.312 | 0.093 | 3.351 | < .001 |
| HeadGaze:Mixed Road:Short Left Curve with Acc. | 0.259 | 0.093 | 2.769 | 0.006 |
| Gaze&Pinch:Bumpy Road:Short Right Curve with Acc. | -0.248 | 0.091 | -2.724 | 0.006 |
| HeadGaze:Bumpy Road:Short Right Curve with Acc. | -0.212 | 0.098 | -2.151 | 0.031 |
| Gaze&Pinch:Mixed Road:Short Right Curve with Acc. | -0.170 | 0.071 | -2.375 | 0.018 |

**Table 15: Significant estimates of the LMM for Selection Offset during Standstill. The intercept is represented by DirectTouch. The estimates describe the distance differences between the listed terms and the intercept in millimeters.**

| Term | Estimate | SE | t | p-Value |
|---|---|---|---|---|
| (Intercept) | 13.826 | 0.210 | 65.961 | < .001 |
| Gaze&Pinch | -2.848 | 0.079 | -36.008 | < .001 |
| Handray | -5.633 | 0.081 | -69.603 | < .001 |
| HeadGaze | -6.207 | 0.082 | -75.641 | < .001 |

**Table 16: Significant estimates of the LMM for Selection Offset during Movement. The intercept is represented by DirectTouch with road type SmoothRoad, and curve type Straight Road. The estimates describe the distance differences between the listed terms and the intercept in millimeters.**

| Term | Estimate | SE | t | p-Value |
|---|---|---|---|---|
| (Intercept) | 13.429 | 0.197 | 68.065 | < .001 |
| Gaze&Pinch | -1.550 | 0.129 | -12.060 | < .001 |
| Handray | -4.032 | 0.136 | -29.612 | < .001 |
| HeadGaze | -4.271 | 0.137 | -31.289 | < .001 |
| Mixed Road | 0.419 | 0.177 | 2.368 | 0.018 |
| Long Left Curve with Acc. | 1.756 | 0.687 | 2.554 | 0.011 |
| Short Left Curve with Acc. | 0.806 | 0.274 | 2.936 | 0.003 |
| Gaze&Pinch:Bumpy Road | 0.665 | 0.273 | 2.436 | 0.015 |
| Handray:Bumpy Road | 0.598 | 0.286 | 2.087 | 0.037 |
| HeadGaze:Bumpy Road | 1.779 | 0.280 | 6.348 | < .001 |
| HeadGaze:Short Left Curve with Acc. | 1.581 | 0.390 | 4.056 | < .001 |
| HeadGaze:Short Right Curve with Acc. | 1.173 | 0.576 | 2.034 | 0.042 |
| Handray:Bumpy Road:Short Left Curve with Acc. | -2.348 | 0.881 | -2.665 | 0.008 |
| HeadGaze:Bumpy Road:Short Left Curve with Acc. | -2.686 | 0.871 | -3.083 | 0.002 |
| Gaze&Pinch:Mixed Road:Short Left Curve with Acc. | 2.637 | 0.990 | 2.662 | 0.008 |

# D GazeMetrics: Vision Aids

**Table 17: GazeMetrics: Accuracy and Precision filtered by utilized vision aids**

| | vision aid | RmsPrecision | AverageAccuracy | SdPrecision.X | SdPrecision.Y | SdPrecision.Z |
|---|---|---|---|---|---|---|
| N | Glasses | 36 | 36 | 36 | 36 | 36 |
| | Nothing | 378 | 378 | 378 | 378 | 378 |
| Mean | Glasses | 0.131 | 1.47 | 0.00510 | 0.00808 | 0.0305 |
| | Nothing | 0.0805 | 1.30 | 0.00718 | 0.00659 | 0.0404 |
| Median | Glasses | 0.0354 | 1.10 | 0.00152 | 0.00170 | 0.0103 |
| | Nothing | 0.0339 | 1.10 | 0.00228 | 0.00176 | 0.00985 |
| SD | Glasses | 0.292 | 1.01 | 0.0104 | 0.0211 | 0.0578 |
| | Nothing | 0.165 | 0.889 | 0.0214 | 0.0169 | 0.0991 |