Effects of Cataracts Severities on Eye Movements and Task Performance During a Visual Search Task Through Virtual Reality Simulations

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Abstract

Visual impairments, such as cataracts, pose a global challenge with preventable cases and unaddressed issues due to limited eye care understanding. In this work, we investigate cataracts using a virtual reality simulation, exploring its impact on a visual search task and investigating the correlations between eye movement features and the severity of the simulation. We simulated cataract progression in one or both eyes through two studies utilizing virtual reality and eye tracking. We analyzed the impact on task performance and eye movements and found that mild cataract progression may be hard to detect. However, more severe cataract simulation revealed significant differences in eye movement characteristics and task performance. These results indicate that eye movements could serve as early diagnostic tools.

CCS Concepts

• **Human-centered computing → Empirical studies in accessibility**; *Human computer interaction (HCI).*

Keywords

Cataract Simulation, VR, Eye Movement

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1 Introduction

Vision loss is increasingly prevalent across the world. Currently, at least 2.2 billion people worldwide experience some form of vision loss, of which nearly 1 billion cases are either preventable or have yet to receive proper treatment [58]. Between 2020 and 2050, the population of people over age 65 worldwide is projected to double from roughly 1 billion to 2 billion [38]. This population aging will have a profound impact on the prevalence of age-related disease, including eye diseases such as cataracts [6]. Cataracts, with 65.2 million affected in 2019 [58], is the leading cause of blindness and the second most common visual impairment after refractive errors. In contrast to refractive errors, cataracts require regular surgery for treatment once diagnosed. However, as the progression of cataracts happens slowly, individuals might only realize they experience the effects of cataracts in a far progressed stadium.

Prior work established that simulations can be used to investigate the effect of visual impairments on task performance [23, 54, 57] and eye movements [17, 21]. Some of the work with simulated visual impairments uses these simulations to evaluate assistive functionalities, e.g., Sipatchin et al. [48]. In the work of Krösl et al. [29], they investigated how to represent cataracts in augmented reality accurately, and in Krösl et al. [28], they investigated the ability of virtual reality (VR) simulation of cataracts to create understanding and nurture empathy towards those that live with cataracts. Simulating visual impairments is therefore crucial, not only to facilitate accessibility research but also to investigate the impact these visual impairments have on day-to-day activities.

In this work, we re-implemented the visual impairment pipeline by Krösl et al. [29] with five parameters that can individually be regulated. We then fine-tuned these parameters to be representative of cataracts by interviewing individuals with cataracts or who recently had cataract surgery. This allowed us to accurately simulate different severities of cataracts and recreate the progression over time. Published work up till now has mostly focussed on creating understanding for those who live with the visual impairment, not only by enabling those without the visual impairment to experience how it is to live with it, but also to replicate everyday scenarios to investigate the accessibility of these (e.g., the emergency sign [28]). In this work, we investigate the effect of simulated VR cataracts on eye movements during a visual search task for household items in realistic scenes to preserve contextual cueing in two user studies.

We used the simulation to extract progression curves for different parameters of the simulation by holding semi-structured interviews and iterative parameter tuning with four individuals who are currently affected by cataracts or recently had cataract surgery (N=4). Following this, we found that when applying one year of simulated progression to the non-dominant eye in a half-hour user study in realistic virtual rooms, participants (N=32) were mostly unaware of the visual impairments, but that this severity of the simulation did not result in changes in eye movements or task performance. Exclusively simulating the visual impairment in the non-dominant eye did not change the task performance. We repeated our study (N=32), where we simulated binocular cataract with progression up to three years as determined by the semi-structured interviews with cataract patients. These findings show several significant differences in task performance and eye movements between the control condition and the Latin square-based conditions.

2 Related Work

First, we provide a short overview of cataracts and how these visual impairments might present themselves in everyday activities. Following this, we highlight how simulations have been used to enhance our understanding of invisible phenomena, highlighting the real-world relevance of vision-related impairments.

2.1 Cataract

Cataracts occur when the eye's crystalline lens becomes clouded [46], blocking light transmission and potentially leading to visual impairment if left untreated. These lens opacities are categorized into three main types based on their anatomical location: nuclear, cortical, and posterior subcapsular. When cataracts develop in the nucleus, patients typically experience increased light scatter and a characteristic yellow discoloration throughout their field of view [36]. In cortical cataracts, protein aggregation causes opacities to form in radial or punctate patterns along the lens periphery [36]. Posterior subcapsular cataracts develop when abnormal lens fiber formation creates opacities near the back surface of the lens, which patients perceive as shadows obscuring central vision [36]. The functional consequences of these cataracts depend on where opacities develop relative to the visual axis and how pupil diameter modulates light entry. Under dim illumination, dilated pupils permit increased straylight to reach the retina, worsening visual performance [53]. Straylight measurements correlate more strongly with cataract severity than standard visual acuity or contrast sensitivity tests, particularly when multiple cataract types coexist [37].

These visual impairments caused by cataracts radically alter visual input and hence cause drastic changes in oculomotor behavior. Wan et al. [55] extensively examined eye movements in visually impaired cataract patients during visual search, face recognition, and reading tasks and discovered disruptions in fixation stability, increased search time, and defective target recognition. Following cataract surgery, patients evidenced significant improvements, including increased fixation counts, longer total fixation durations, and smaller proportions of regressive saccades, all indicative of better visual attention and more efficient visual processing. Similarly, Thepass et al. [50] reported that advanced cataracts specifically slow down saccadic reaction times and decrease visual field sensitivity, both of which show significantly improved function following surgery. Compensatory mechanisms in visually impaired individuals were also discovered by Fine and Rubin [17], demonstrating altered patterns of fixation that compensate for visual loss, particularly when reading. Kalia et al. [25] also showed remarkable improvement in accuracy of eye movements in patients with congenital cataracts after surgery, establishing vision restoration as a demonstration of the neuroplasticity of oculomotor control. Collectively, these studies affirm the reversible and intricate nature of cataract effects on eye movement parameters and visual function.

2.2 Simulations to Enhance Understanding

The emergence of consumer VR technology has recently unlocked new ways to enhance learning and comprehension through immersive simulations. One such example is ElectroVR, an interactive tool developed by Greenwald et al. [19], which enables users to engage with the principles of electrostatics within a shared virtual environment, providing a novel way to visualize an otherwise invisible phenomenon. Similarly, Greenwald et al. [20] introduced CrystalVR, designed to facilitate the examination of intricate crystal structures that are typically difficult to visualize. Additionally, Knierim et al. [26] created a mixed reality application that overlays false-color temperature visualizations onto metal objects, thereby augmenting the perception of thermal conductance. These systems all use the immersive potential of VR to render complex or abstract concepts more tangible and easier to understand, offering insights that traditional methods struggle to convey.

In accessibility, simulations have been used to evaluate designs and inform designers. Rousek and Hallbeck [42] employed simulation goggles representing different visual impairments to evaluate wayfinding design within a healthcare facility, identifying several design deficiencies. Similarly, Väyrynen et al. [54] focused on architectural designers by utilizing a VR headset to simulate various visual impairments while participants navigated a virtual environment. Their findings indicated that simulations serve as an effective tool for providing designers with a general understanding of the challenges experienced by individuals with visual impairments. Beyond designs, simulations have also been used to raise awareness and increase empathy. An example is the demonstrator of Lang et al. [31], where they use a gaze-contingent simulation for central field loss, aiming to raise awareness rather than conduct user studies. Sipatchin et al. [48] developed a more complex vision impairment simulation using a scotoma texture, whereas Kwon et al. [30] applied image-processing effects to simulate eye disease patterns, though without gaze-contingency or VR integration. These visual simulation works help identify design flaws and foster empathy.

Simulations have also been used to simulate cataracts. Krösl et al. [28] examined the maximum recognition distance threshold in a cataract simulation. Other simulations, such as those by Wood et al. [56] and Almutleb and Hassan [1], used specialized eyewear or contact lenses to mimic conditions like cataracts or glaucoma. In VR, Lewis et al. [32] and Lewis and Shires [33] introduced impairment simulations where symptom severity was not adjustable. Although simulations have been extensively used to investigate the impact of other visual impairments like glaucoma or age-related macular degeneration on task performance and eye movements, to the best of our knowledge, no such studies exist for cataracts.

3 Cataracts Simulation Implementation

For our simulation, we re-implemented the effects pipeline by Krösl et al. [29] in Unity using the five parameters: reduced VA, contrast loss, color shift, loss of peripheral vision, and sensitivity to light.

3.1 Contrast Loss

The work from Krösl et al. [29] already implemented a reduced contrast using gray interpolation. Additionally, we re-implemented the compression of the luminance value from Krösl et al. [28]; allowing for more control in simulating the mechanism of the human eye since it is implemented in the *CEILAB* color space (also referred to as $L^*a^*b^*$). This is because adjusting RGB color channels linearly does not produce linear changes in contrast [28]. To reduce the contrast by compressing the luminance, the RGB value of each pixel needs to be transformed into the *CEILAB* color space first. After this, we can apply the following formula $L = L_1 \times l + 50 \times (1 - l)$ where L represents the new luminance value, L_1 the initial luminance, and $l \in [0, 1], \quad l \in \mathbb{R}$ as a scaling factor. To preserve the average lightness $50 \times (1 - l)$ is added [28]. We visualize this in Figure 1d.

3.2 Color Shift

While Krösl et al. [29] implemented a color filter, we additionally re-implemented the interpolation by Krösl et al. [28]. We implemented this option as it seems to be more representative of online visualizations used to illustrate cataracts. Hence, we implemented both to be evaluated in interviews later.

3.3 Sensitivity to Light

As Krösl et al. [29] used Unreal Engine, we could not use the same bloom post-processing. Instead, we used the Bloom effect provided by Unity as it is a similar post-processing effect. This processing effect allows us to manipulate the light's intensity, threshold, and diffusion. These allow us to simulate the effect of images blurring, with bright lights proving especially problematic due to the intense glare they produce [28]. In Figure 1g, we visualize this part of our effects pipeline.

3.4 Loss of Peripheral Vision

Lastly, cataracts result in lens clouding. While for nuclear cataracts, this clouding spans the entire lens uniformly, subcapsular cataracts are often visualized as a dark shadow in the center of the lens, and cortical cataracts are often visualized as a dark shadow in the periphery of the lens. We simulate this loss of peripheral vision using a gaze-contingent stencil shader implementation that hides items with a specific material. This results in hidden items outside the area (i.e., in the peripheral). We chose this approach as we found during pilot testing that participants always perceived these dark shadows simulations that other work had used [28, 29], even when these changes were minimal. This is the case as current hardware cannot keep up with human perception regarding refresh rate and latency, thus making it unsuitable for our study. Figure 2 visualized the loss of peripheral vision from our pipeline.

4 Cataracts Simulation Validation

In an effort to validate our implementation of the different cataract parameters and the progression of cataracts, we held semi-structured interviews with individuals who either currently have cataracts in one eye or recently had cataract surgery. The interviews all consisted of two parts: demographic questions and, following this, an iterative parameter adjustment. All were done over video call or in person on a normal screen.

4.1 Procedure

We prepared a sample scene with a low-poly landscape for the iterative parameter adjustment according to Section 3. Before the interview, we sent out the consent forms and a copy of the procedure so the participants had ample time to read through them before participating in the interview. One interview took place in person, and the remaining was over video call. At the start of the interview, we asked if the participant had any questions about the consent form procedure. After this, we started off with a series of demographic questions relevant to the study at hand. After the demographic questions, we came to the iterative parameter adjustment. During the iterative parameter adjustment, we inquired about the different implementations for contrast loss and color shift, which are more capable of recreating their visual perception. We did not represent the loss of peripheral or central vision using the stencil shader approach; instead, we applied a vignette or inverted vignette effect, as the stencil shader effect is not "visible" and therefore, participants were unable to indicate the size accurately. During the iterative parameter adjustment, we used the sliders to adjust the parameters to recreate the participants' visual impression of their cataracts. First, one by one, after which all parameters are combined, as some affect each other.

4.2 Participants

In total, we interviewed six individuals who either currently have cataracts in one eye or recently have had cataract surgery. Two participants were excluded as one reported to have far progressed age-related macular degeneration, which is more influential to their vision, and one participant was excluded as they reported the progression of cataracts to happen within the span of one month, which contradicts existing literature [35]. For the remaining four participants, P1 (female, 82 years old) reported -2 dioptri in the right eye, where the last cataract surgery was in 2014. P2 (male, 74 years old) was interviewed after recent cataract surgery; during that interview, there was no reported loss of vision. P3 (female, 56 years old) reported < 5% vision remaining in her right eye, where she had cataract surgery last performed in 2008. However, her vision was affected by several other vision impairments. P4 (male, 68 years old), interviewed after recent cataract surgery, reported +2.5 dioptri in both eyes. Unfortunately, none of the participants reported the exact type of cataracts.

(a) Reference Image (b) Gaussian Blur (c) Interpolation with Gray (d) Luminance Reduction

(e) Color Interpolation (f) Simulated Color Filter (g) Sensitivity to Light (h) Effects Combined

Figure 1: A low-poly landscape illustrating individual and combined cataract effects: (a) No visualization. (b) Loss of visual acuity [29]. (c) Interpolation with gray [29]. (d) Luminance reduction. (e) Color interpolation. (f) Simulated color filter [29]. (g) Sensitivity to light. (h) All effects combined.

4.3 Interview Results

During the interviews, we found that all participants reported that the interpolation with gray (see Figure 1c) is more representative of the loss of contrast and that the color interpolation (see Figure 1e) is perceived to be more representative of the color shift. All participants went through the iterative parameter adjustments until they found that this represented their perception (either in the cataracts-affected eye or while it was affected).

We visualize their reported cataracts progression over time in Figure 3. For every parameter respectively, we do not plot those where the parameters were not present. Furthermore, we visualize all parameters' average progression over time using the dashed lines. By doing so, we assume a linear growth of each parameter, as we could not collect data about progression over the span of multiple years[1]. None of our participants report any loss of peripheral vision. Lastly, the years of progression were reported by the participants, but we noted substantial variability between individual experiences, highlighting the personalized nature of cataract progression. We acknowledge that these participant' estimates of progression might not be fully accurate due to their retrospective and subjective nature; however, given the absence of objective historical data or continuous longitudinal recordings, this remains the most feasible and practical approach currently available.

5 Cataracts Simulation Minimal Noticeable Differences

While cataracts traditionally present themselves in both eyes, our goal in this study is to visualize minimal progression to (1) investigate if participants notice the changes and (2) investigate if these changes affect eye movements and task performance before the participants become aware of the presence of the simulation. As such, in the following section, we showed the simulation exclusively in the non-dominant eye, as participants are less likely to notice the change [41]. In this and the following study, we chose to simulate cataracts rather than recruiting participants already affected by cataracts for three reasons. (1) Those affected by cataracts are sensitive to light, in VR this would mean exposing them to the LUX output of the headset, which can be uncomfortable for them. Furthermore, (2) simulations allow us to maintain precise control over the progression and severity of visual impairment. Simulations allow us to systematically vary the degree of cataract opacity and closely monitor subtle changes in participants' visual experiences, which would be challenging with individuals naturally affected due to variability in progression and subjective experiences. Finally, (3) simulations enable us to isolate and specifically investigate the early stages of cataract development and their initial impact on visual perception and behavior, offering clearer insights into early detection and management strategies.

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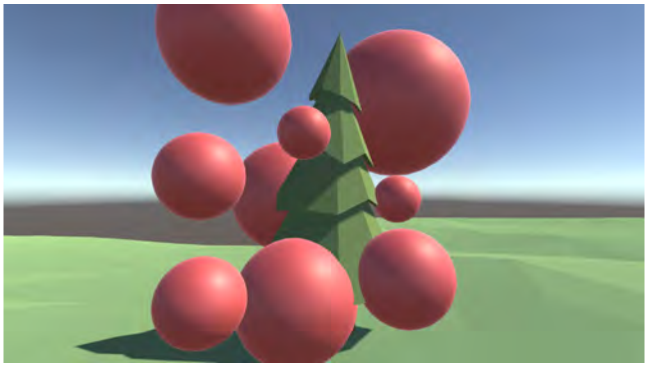
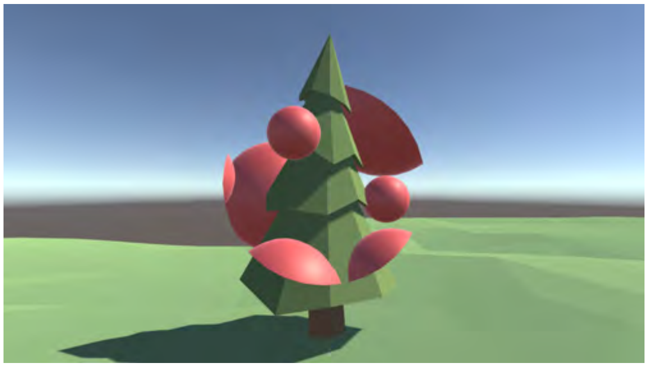
[1] We acknowledge that this might oversimplify the progression of cataracts.



(a) Normal Vision



(b) Peripheral Vision Loss

Figure 2: A low-poly landscape with (a) normal vision and (b) gaze-contingent peripheral vision loss, where red balls disappear outside the visible area.

5.1 Apparatus

We selected a visual search task to assess the impact of the cataract simulation on participants' behavior and performance. Visual search tasks have been employed widely to investigate visual impairments both on patients with visual impairments [13, 40] as well as in simulations of visual impairments [14, 24, 30]. Pollmann et al. [40] showed that participants with Age-Related Macular Degeneration are significantly less deficient in search tasks compared to healthy participants in realistic scenes (such as rooms in a home) due to the possibility of contextual cueing. This shows that displaying realistic scenes is necessary to adequately assess the deficiencies of visual impairment in search tasks. Therefore, we opted to show realistic environments of different rooms in the virtual environment. Similar to David et al. [14], we built eight virtual environments to represent different rooms in a house; see Figure 4. We ensured that luminance in all rooms was consistent, see Section A.1.

For the search items, we used items that could be found in a household, namely, an apple, calculator, rubber duck, first aid kit, flashlight, glass, hairdryer, kettle, medicine bottle, phone, screwdriver, soap bar, or stapler. All rooms and items were chosen to preserve contextual cueing.

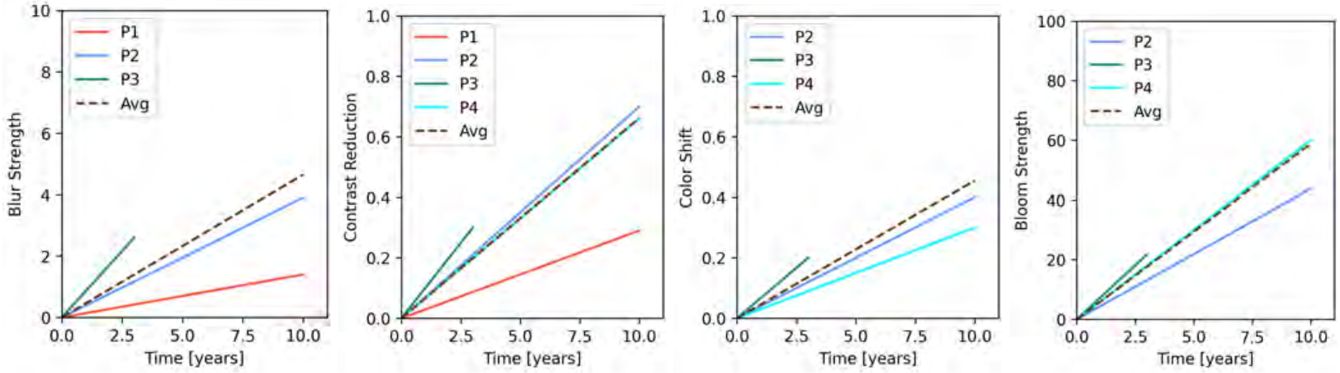
We built the virtual environments in Unity3D and deployed it to a desktop with a Ryzen 9 7900X3D, 64GB RAM, an NVIDIA RTX 4080 Super graphics card, and a connected HTC Vive Pro Eye with a built-in Tobii eye tracker. The HMD has two AMOLED screens, with a resolution of 2.880 × 1.600 pixels in total (1.440.600 pixels to each eye, resulting in a pixel density of 615 pixels per inch (PPI)), with a native refresh rate of 90 Hz and a field of view of 110°. The built-in Tobii eye tracker was accessed using the Vive SRanipal SDK at a sampling frequency of 120 Hz.

We collected the head position and directional 3D vectors from Unity. We recorded eye tracking data using the built-in eye tracker in the HTC Vive Pro Eye (120Hz) through the SRanipal SDK, giving us eye-directional 3D vectors relative to both the world and the head. To facilitate our analysis, we converted the head directional 3D vectors, eye-in-world directional 3D vectors, and directional 3D vectors into 2D Fick angles using the Fick-gimbal method [22]. This transformation applies two sequential rotations (vertical axis followed by a nested horizontal axis) to characterize the position of each vector. These resulting 2D Fick angles for eye and head directions served as the foundation for our subsequent analysis. For the analysis, we focused on the eye tracking data for each trial. Our trials were relatively brief, with a mean duration of 5.3 ± 8.89 seconds, leading us to perform eye tracking analysis at the trial level instead of examining behaviors within individual trials.

We calculated fixations and saccades using pymovements [27], an open-source Python package for analyzing eye-tracking data. We leveraged pymovements' implementation of the ID-T algorithm [43] with specific fixations thresholds set at a minimum fixation duration of 83 ms and a maximum dispersion of 1.8°, in line with prior work [4, 10, 52]. From this, we derived fixation metrics including: total fixation duration, average fixation duration, fixation count, and latency to the final fixation in each trial. For saccades, we again leverage pymovements, this time for its implementation of the microsaccade algorithm [16]. This algorithm allows us to calculate the saccadic amplitude and saccade frequency. We defined saccadic amplitude as the angular displacement in degrees from onset to offset, and computed saccadic frequency by dividing saccade count per trial by trial duration in minutes. To calculate the average pupil dilation for each trial, we computed the mean of the left and right pupil sizes and subsequently calculated the standard deviation to facilitate our analysis at the trial level. Finally, for computing the Index of Pupillary Activity (IPA), we employed the implementation by Duchowski et al. [15]. Thus, we utilized discrete wavelet transforms to analyze pupil diameter signals, specifically employing a two-level discrete wavelet transform. We normalized the wavelet coefficients to ensure a uniform analysis and identified key extremes in the signal to mark significant changes in pupil diameter. We then applied a universal threshold to filter out noise.

5.2 Procedure

The study coordinator first welcomed the participants and, after signing the consent form, asked them to answer a few demographic questions. The coordinator then introduced and explained the study procedure. Namely, they were tasked with searching for household items in 8 rooms. Additionally, the study coordinator told the participant that we would manipulate something throughout the study, and if the participant noticed, they should report it. Afterward, the coordinator and participant determined the dominant eye using the



(a) Progression of VA reduction **(b) Progression of contrast reduction** **(c) Progression of color shift** **(d) Progression of light sensitivity**

Figure 3: The progression of the different parameters over the years. Each line represents the progression for one interviewee, where the colors are consistently representing the same participant throughout the graphs. Where interviewees did not report a progression of one parameter, this is not represented in the data. The dashed line represents the average linear progression over 10 years.

Dolman method [8]. Finally, before entering VR, the study coordinator explained the hardware and controls relevant to the study to the participants.

After putting on the HTC Vive Pro Eye, the study coordinator navigated the participant to the integrated eye-tracking calibration. After which, the experiment was started. For each trial, we present the item the participant was tasked with finding on a gray background. Once the participant confirms, the item spawns at a random location in the room. These spawning locations were randomly assigned throughout the room, and potential collisions with other items were checked. If there was a collision, a different spawning location was selected. This was then repeated for 15 items in each room. We increased the severity of the simulation linearly after each trial, except for when the participant moved from one room to the next for the participant in the *linear increase* condition. For the control condition, there was no change. In the linear increase condition, the participants all started without any cataract simulation and ended with a simulation severity of 1 year as determined in the interviews (see Section 4.3). As the participants were made aware that we would manipulate something throughout the study, they were asked to report anything they noticed that was off from how they expected it to be. If they did not actively report to the study coordinator before the end of the study, the study coordinator asked them specifically if they noticed something odd.

We applied a drift correction after each room, following Sipatchin et al. [49]. This drift correction was designed to compensate for eye tracking data quality decay in VR due to the participant's movement, which is known to induce drift into the precision of the eye tracker [11]. These drifts can influence the gaze-contingent simulation of the peripheral loss.

5.3 Participants

We conducted our study with 33 participants, ages 20 to 71 (mean = 27.6, std = 10), with 14 identifying as male, 19 as female, and none as non-conforming. Six participants wore contacts during the experiment. The remaining participants had normal vision, with 19 being rightly dominant-eyed, and 15 had a left dominant eye, as determined by the Dolman method. 20 participants were part of the *linear increase*, while the remaining participants were part of the control condition. One participant in the *linear increase* condition was excluded as their eye tracking data was incomplete. While we recognize the imbalance between the two conditions, our analysis methods are robust against this imbalance [39]

5.4 Results

In this section, we first present the findings of how our simulation affects eye movements, among others, while being influenced by the cataract simulation, see Figure 5. We employ the Bayesian Independent Samples T-Test to compare the slopes of fitted linear regressions over the severity.

5.4.1 Preprocessing. We had a total of 3840 trials (120 trials per participant). Following this, we filtered out trials where the participants had excessive head movements as we were interested in gaze. We define excessive head movements as trials where the participant moves their head 15 cm higher or lower than the overall average across all trials. We also filtered out trials where the participants did not look at the object they were supposed to search for. To do this, we took the maximum angular diameter of the object, i.e., if the object was not perfectly square, we took the largest measurement of the height, width, or length. Using the following formula: $\delta = arctan\left(\frac{d}{2D}\right)$, we calculated the maximum angular diameter of each sample δ. Then, we compared the absolute angle of the gaze to the center of the object during the trials and the angle at which the object took us in the virtual environment. If, in the last ten samples of a trial, more than 50% of the absolute gaze angle was higher than 180% of δ, trials were discarded. Lastly, we excluded trials that were more than 20 seconds. After preprocessing, we had a total of 3616 trials remaining.

(a) Bathroom **(b) Bedroom**

(c) Dining Room **(d) Garage**

(e) Kitchen **(f) Living Room**

(g) Meeting Room **(h) Office**

Figure 4: Our realistic virtual environments used for the user study. On the left, no vision impairment was simulated. On the right, one year of cataract progression is simulated.

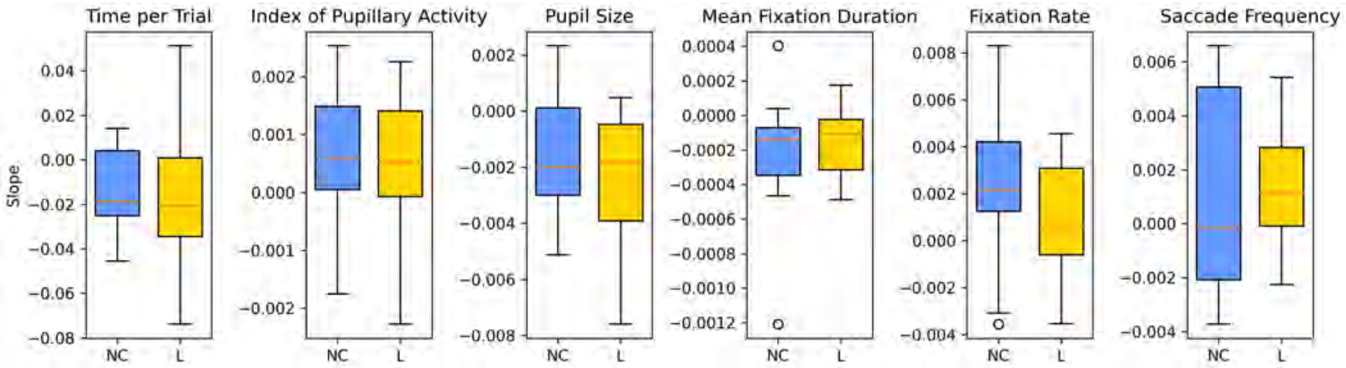


Figure 5: The results of our different measurements. NC (non-cataract), L (linear increase of the simulation)

5.4.2 Bayesian Results. We fit a linear regression for each participant over the different extracted eye-tracking characteristics to compare the two conditions (linear increase of simulated cataract severity and control). As we expect that there will be a learning effect throughout the user study and per room, we compared the slopes of these regressions using Bayesian independent sample t-tests. Thus, we conducted a Bayesian independent sample t-test using JASP. Priors for all tests were set to be Cauchy (location = 0, scale = 0.707), with our alternative hypothesis being that the slopes from linear change and control are not equal. We found $BF_{10} = 0.103$, $error~\% = 0.166$ when including all the different extracted eye-tracking characteristics. This indicates strong evidence that the slopes of the linear change and control are equal. We further explored the data by looking at individual eye-tracking characteristics. Our results show anecdotal to moderate evidence that the slopes of the linear change and control are equal (H_0). However, when exclusively looking at the fixation slope and fixation rate, we find anecdotal evidence for the slopes being different (H_1). We report the results of all our tests in Table 1. We checked if normalizing the participants' variance showed differences compared to the slopes reported; however, running the same test with the z-score normalization increases the evidence for the data being from the same population.

Out of the 19 participants included in the final results with the linear increase, we found that 60% of these participants (12) were unaware of the simulated visual impairment at the end of the user study. This means they were unaware of the progression that normally would happen over a year in 30 minutes. Of those who did notice the simulated cataracts, 6 participants noticed it in the second half of the study. All of those who noticed described the loss of VA as noticeable. At the same time, none of the participants reported having seen any of the other effects, even when explicitly asked for it at the end of the user study.

5.4.3 Interim Discussion. We found that most participants were unaware of the simulation of cataracts. Given how we have developed the virtual environments, this articulated the established finding that contextual cueing influences the ability of those with simulated visual impairment to find objects [40]. This echoes the importance of implementing realistic scenes and items to investigate simulated visual impairments. Furthermore, we found that 60% of our participants were completely unaware of the simulation representing the progression of one year of cataracts in the study of 30 minutes. Since participants were unaware of the progression, we expect that, since the progression happens much slower, individuals who experience cataracts will be unlikely to notice it themselves, even after several years of progression. This is corroborated by our interview findings, in which one of our participants mentioned that they were unaware of their cataracts; however, the doctor diagnosed < 5% of residual vision. This expresses the need for detection methods for visual impairments, as when the individual notices the visual impairment, it might already be in a far progressed state.

When analyzing the eye tracking characteristics, we found no differences between those who experienced a linear increase in severity and those in the control condition. More precisely, we found strong evidence that these are equal, which could be attributed to the learning effect of gradually increasing the simulation. While we manipulated the severity of the cataract simulation over one year, we did not investigate further progression or binocular cataract

Table 1: Bayesian Independent Samples T-Test

	$\mathbf{BF_{10}}$	**error %**
Time	.345	.009
IPA	.350	.003
PD	.420	.010
Fixation		
Count	.407	.011
Disp. Area	.671	<.001
Avg. Dur	.400	.012
Std. Dur	.375	.013
Tot. Dur	.368	.013
Var. Dur	.552	.017
Slope	1.423	<.001
Rate	1.014	<.001
Saccades		
Amplitude	.346	.009
Freq.	.338	.007

simulation. As such, in the second user study, we will increase the severity and change the paradigm to binocular.

6 Cataracts Progression Simulation

In Section 5, we saw that the potential learning effect outways the visualization of cataracts when gradually increasing the simulation in the non-dominant eye. In this follow-up, we simulate up to 36 months of progression in 8 conditions using a Latin square balanced experimental paradigm. Varying from no simulation up to 36 months of progression in equal increments following the results of the Section 4.3. In the remainder of this section, we discuss the user study performed with 32 participants. The apparatus and procedure are the same as Section 5.

6.1 Participants

We recruited 34 participants for the evaluation. However, we had to exclude two participants (one for technical issues and one who did not follow the instructions). The remaining 32 participants, ages 19 to 68, had a mean age of 27.3 ($SD = 10.2$), 16 identifying as female, and 16 identifying as male. All participants had normal or corrected-to-normal vision through contact lenses. Finally, none of the participants participated in the first user study.

6.2 Results

In this section, we first present the results of our preprocessing. After which, we present the findings of how our simulation affects eye movements and task performance while being affected by different severities of our cataract simulation.

6.2.1 Preprocessing. After extracting the relevant eye tracking characteristics following Section 5.1. After all filtering, we were left with 3149 trials. 402 trials for no visualization, 406 for 5.1 months of progression, 400 for 10.3 months or progression, 410 for 15.4 months of progression, 371 for 20.6 months of progression, 395 trials for 25.7, 401 trials for 30.9, and 364 for 36 months of progression. To investigate if there is an effect in the remaining number of trials after preprocessing, we used a Bayes repeated measure ANOVA in JASP with default prior scales to estimate the likelihood of an effect. This resulted in a $BF_{10} = 0.05$, thereby providing strong evidence for the absence of an effect.

6.2.2 General Linear Mixed Model Results. We use generalized linear mixed-effect models (GLMMs) to analyze the data from our experiment allowing us to account for the complex experiment design by using random effects for individual variability, rooms, objects, spawning locations, or learning effects and is particularly suited for our data as it is non-normally distributed and allows for a repeated measures design [7, 47]. For each dependent variable, we include a brief description of each part, including their observed distribution (i.e., corresponding distribution family). These distribution families are selected based on comparing all possible distributions against the data and selecting the best-fitted one. For each dependent variable, our formula was $DV \sim condition + (1|Room) + (1|Object) + (1|Location) + (1|TrialNr) + (1|Pid)$ where DV is our dependent variable and condition is the 8 different months of cataract progression. We conducted our analysis in R with lme4 [3]. We report conditional R^2 as R^2_c and marginal R^2 as R^2_m.

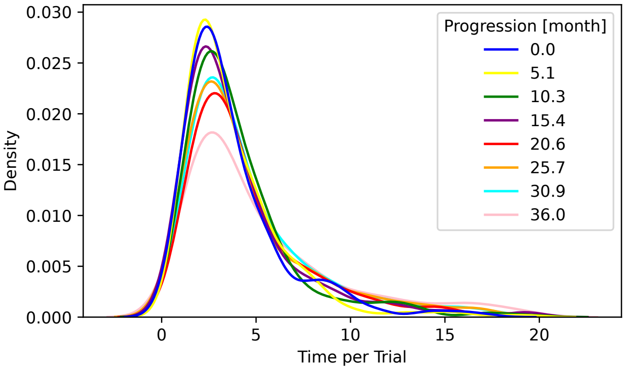


Figure 6: Kernel Density Estimate of time per trial for progressions.

In Table 2 and Figure 6 we highlight the results of our GLMM with regards to the time per trial under the different conditions, showing the increase in the time required for each trial as the severity of the simulation increases. We also observe an increase in fixation rate as the severity of the simulation increases (see Table 2 and Figure 7). We furthermore found decreases in saccade amplitude (see Figure 8) and saccade frequency (see Figure 9), both also mentioned in Table 3. Finally, when looking at pupillometry we observed changes in both pupil size (see Figure 10) and the IPA (see Figure 11), both also mentioned in Table 3.

7 Discussion

In this work, we first implemented a simulation for cataracts in Unity3D that allows for precise manipulation of five parameters mostly based on the work of Krösl et al. [29]. We validated the

Table 2: Results of the GLMM analysis for the time per trial, fixation rate, and mean fixation duration under different central-field loss conditions. We used the inverse gaussian family and identity link for the time per trial and mean fixation duration. For the fixation rate, we used an inverse Gamma family with an identity link. * intercept – Time Per Trial: estimate = 4.41, Mean Fix. Duration: estimate = 0.15, and Fix. Rate: estimate = 3.65.

	Time Per Trial		Fix. Duration		Fix. Rate	
Prog.	**t**	**p**	**t**	**p**	**t**	**p**
0 *	10.54	<.001	18.63	< 0.001	28.08	<.001
5.1	1.46	.143	1.25	.265	3.52	<.001
10.3	2.29	.022	1.16	.450	1.14	.254
15.4	1.98	.048	1.40	.140	2.06	.039
20.6	5.08	<.001	2.11	.135	0.52	.602
25.7	2.62	.009	2.15	.132	2.58	.010
30.9	4.34	<.001	2.20	.128	3.86	<.001
36.0	6.00	<.001	1.28	.201	5.05	<.001
	$R^2_c = 0.72$ $R^2_m = 0.50$		$R^2_c = 0.11$ $R^2_m = 0.02$		$R^2_c = 0.59$ $R^2_m = 0.30$	

accuracy of our simulation in interviews with individuals who either currently have cataracts or recently had cataract surgery. In these interviews, we asked the interviewees to manipulate the parameters to represent their perceived vision while being affected by cataracts. By doing this, we could represent a progression curve over time. We then used this progression curve for a user study, simulating cataracts progression over one year in the non-dominant eye of participants while they were searching for everyday items in realistic scenes. In the interim discussion, we highlighted that while the participant was mostly unaware of the linear increase in severity of the simulation, even though we told them about potential changes they could experience. We further were unable to find differences in task performance or eye movements. To follow up on this, we did another user study where we simulated binocular cataracts in a Latin square-balanced experiment, where we had up to 3 years of progression visualized. In the following, we discuss the most critical implications of our work. These include the representation of visual impairment simulations and the implications to future work when considering the effect of visual impairment simulation on eye movements.

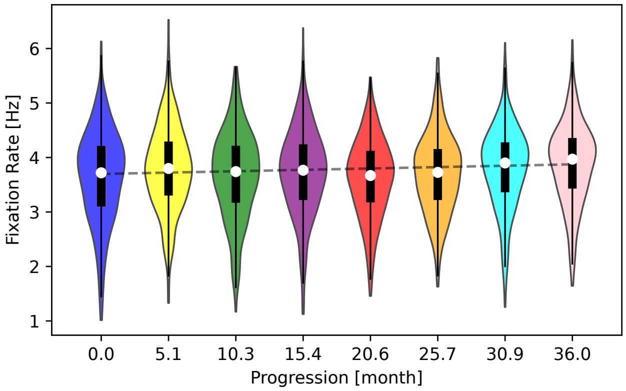


Figure 7: Fixation rate for each cataract simulations.

Table 3: Results of the GLMM analysis for saccade amplitude, saccade frequency, pupil size, and IPA under different cataract progression conditions. We used the inverse Gaussian family with an identity link for pupil size. The saccade amplitude, saccade frequency, and IPA models used an inverse Gamma family with an identity link. * intercept – Sac. Amplitude : estimate = 27.51 , Sac. Frequency: estimate = 2.87, Pupil Size: estimate = 4.66, and IPA: estimate = 0.65.

	Sac. Amp.		Sac. Freq.		Pupil Size		IPA	
Prog.	t	p	t	p	t	p	t	p
0 *	19.58	<.001	28.33	<.001	23.50	<.001	21.06	<.001
5.1	−3.17	.002	0.06	.956	−12.40	<.001	−0.62	.536
10.3	−1.53	.125	−1.54	.124	−14.79	<.001	−0.92	.358
15.4	−1.54	.123	−3.08	.002	−23.48	<.001	−1.67	.094
20.6	−2.70	.007	−1.33	.183	−25.12	<.001	−1.84	.049
25.7	−2.08	.037	−1.39	.166	−34.14	<.001	−2.11	.035
30.9	−3.90	<.001	−2.90	.004	−37.71	<.001	−2.92	.004
36.0	−5.36	<.001	−2.34	.019	−42.47	<.001	−3.41	<.001
	$R_c^2 = 0.99$ $R_m^2 = 0.70$		$R_c^2 = 0.40$ $R_m^2 = 0.13$		$R_c^2 = 0.40$ $R_m^2 = 0.13$		$R_c^2 = 0.96$ $R_m^2 = 0.54$	

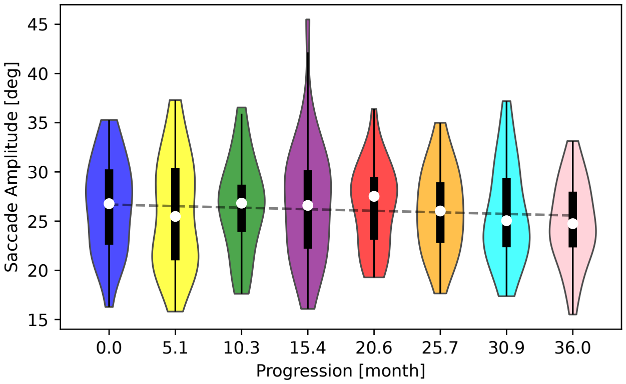


Figure 8: Saccade amplitude for each cataract simulations.

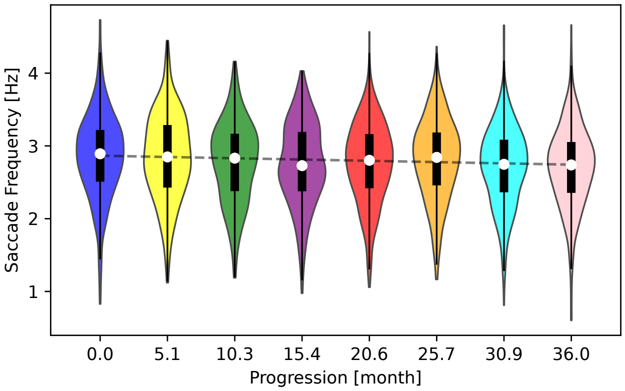


Figure 9: Saccade frequency for each cataract simulations.

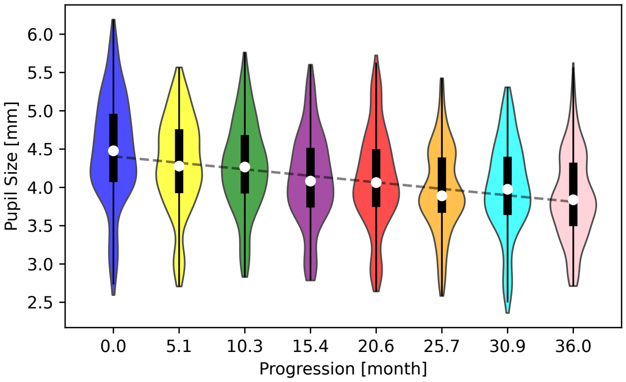


Figure 10: Pupil size for each cataract simulations.

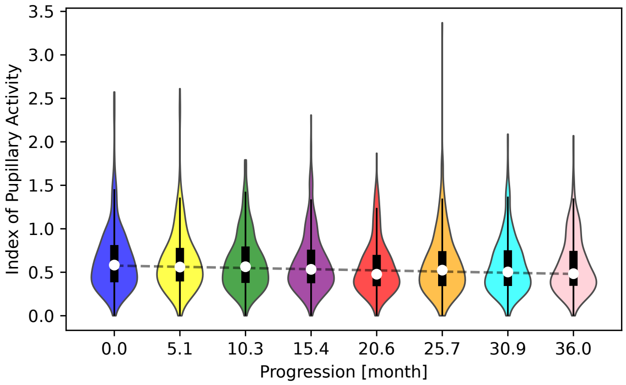


Figure 11: Index of Pupillary Activity for each cataract simulations.

7.1 Quality of Cataract Simulation

The results of our interviews highlight that our simulation can visualize different severities of cataract progression and that this can reproduce the vision perceived by those who either have cataracts or recently had surgery. However, future work should investigate a broader spectrum on individuals with various progression stages. We achieved a simulation that is representative of the perception of those interviewed by using different effects, which allow the manipulation of parameters to represent the different aspects of cataracts accurately. For future work in visual impairment simulations, validating the simulation by interviewing specialists and/or patients is important. For cataract simulations specifically, we have made our simulation scripts available for future work to be used and extended, see Section 8.

7.2 Impact on Task Performance and Eye Movements

The findings of this study reveal significant differences in task performance across different cataract simulation severities compared to the control condition, with the more severe cataract simulations resulting in longer visual search task times (Table 2). We observed significant changes in fixation rate (Table 2), a significant decrease in saccade amplitude (Table 3), alongside significant differences in saccade frequency (Table 3), a significant decrease pupil size (Table 3) and decrease in IPA (Table 3). We did not find a significant difference in mean fixation duration. Although participants made more errors in the higher severity cataract simulation, there was strong evidence against any condition-related effect on trial retention.

Several studies have previously observed altered eye movement behavior in those with visual impairments and have linked these abnormal eye movement behaviors to functional difficulties in daily activities [34]. An example of this is the high fixation instability in people with AMD, which was suggested as the main contributing factor for their poor visual acuity, face recognition, and reading ability [2, 9, 44]. In investigations of eye movements in glaucoma, eye tracking has become a tool to evaluate the effect of glaucomatous visual field defects on the ability to do everyday tasks [18, 45]. However, there is sparse research on investigating eye movements in cataract.

With cataract, previous work has demonstrated the impact on task performance, in the work of Wan et al. [55] they showed that pre-operation individuals took significantly longer in a visual search task compared to post-operation. In line with our findings, previous studies have also demonstrated altered eye movements in patients with cataract before and after surgery [50, 55]. In our task, participants had a significantly higher fixation rate, but we did not find a significance in mean fixation duration. These findings are in line with those of Wan et al. [55]; here, they reported a significant increase in fixation count and total fixation duration in a visual search task but did not find differences in the mean fixation duration between pre and post-operation.

For glaucoma, it has been proposed that information from eye movements might be useful for detecting visual impairment [12]. Given that the findings from our work are in line with those who investigated cataract pre and post-surgery, our simulation adds value for future research. It allows for controlled environments to test how changes in eye movements manifest over time and with different severities by simulating various stages of cataract progression. This allows researchers to explore scenarios, explore early detection mechanisms from eye movements, and investigate adopted mitigation strategies for cataract before the need for clinical trials.

7.3 Future Work & Limitations

To the best of our knowledge, no previous study has quantified eye movement parameters in everyday tasks under a VR cataract simulation. Future research must further advance these simulations with additional factors, such as non-uniform cataract simulations. These future simulations must also be validated by including those affected by cataracts in order to establish their validity. Simulation research alongside clinical research in cataract patients will enable future work to compare simulated outcomes against actual patients' qualitative and quantitative experiences. Ongoing validation through real-world data and patient reports will help ensure simulations are true reflections of cataract patients' actual visual sensations, potentially making early detection methods better.

A limitation of this study is that our VR-based simulation may not fully capture the complexities of real-world visual impairments. While the controlled, high-fidelity environment allowed for precise manipulation of visual conditions, it lacks real-world variability, such as fluctuating lighting, environmental distractions, and physical object interactions. Moreover, conditions like cataracts involve dynamic and fluctuating vision loss, which is difficult to replicate accurately in a static simulation. Our study was conducted within a single session, limiting our ability to assess long-term adaptation or the role of compensatory sensory cues (e.g., tactile or auditory input). As a result, the findings may overestimate or underestimate the actual impact of visual impairments on real-world search performance.

Additionally, while simulations provide valuable insights into task performance and eye movements, they often fail to account for the adaptive strategies developed by individuals with visual impairments over time. People with disabilities refine scanning routines, systematic object placement, and other strategies that allow them to navigate daily tasks effectively—adaptations not captured in short-term simulations. Consequently, nondisabled participants may perceive simulated tasks as disproportionately difficult, reinforcing misconceptions about the lived experiences of visually impaired individuals [51]. It is crucial to acknowledge that simulations cannot replace the nuanced expertise and adaptive skills of those with lived experience. Future research should integrate participatory methods, directly involving individuals with AMD to explore their strategies and inform the design of supportive interventions [5]. By prioritizing co-design and firsthand experience, like designing the simulation to be accurate to the reported perception of those affected, researchers can move to informed solutions that address genuine community needs [5].

8 Conclusion

We present a systematic investigation of how to implement a cataract simulation and validate this simulation with individuals currently experiencing cataracts or recently undergoing cataract surgery. In the subsequent study, we used this simulation to simulate the progression of cataracts in a realistic VR environment where individuals participating were tasked with searching for household items. We found strong evidence for eye movement characteristics being the same for those with linearly increasing severity and the control condition. Furthermore, we noted that most of the participants in this user study were unaware of the simulation. In the second study, we investigated the effect of a binocular cataract simulation on eye movements and task performance and found significant differences in line with previous work investigating cataract patients pre and post-surgery. Our findings lay the groundwork for future simulation studies, echoing the necessity for realistic virtual environments and validation of the simulation with patients.

Open Science

We encourage readers to reproduce and extend our results and analysis methods. Therefore, our simulation scripts, collected data, and analysis scripts are available at https://osf.io/q2yms/. Furthermore, we have a living project on GitHub of the unity project at https://github.com/mimuc/VIS.

Author Contributions

Jesse W. Grootjen: Conceptualization, Formal Analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing; **Yannick Weiss, Tobias Daniel and, Fabian Kahman**: Conceptualization, Formal Analysis, Investigation, Methodology, Writing – original draft; **Sven Mayer**: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – original draft, Writing – review & editing.

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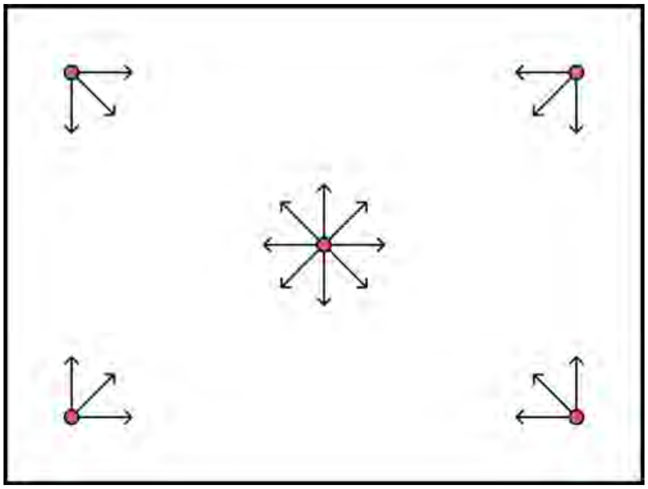

Figure 12: Lux calibration points and directions

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A Appendix

A.1 Room Luminance

To ensure that the lighting in the different rooms was not a confound in our work, we ensured a similar luminance level was maintained in each room. We measured the luminance from the headset by positioning a LUX meter (MT-912 light meter) inside the HTC Vive Pro Eye HMD. We placed 5 points in each room, 4 in each corner, and one central to ensure the lighting was similar. For the 4 in the corner, we measured the lighting conditions in 3 steps of 45°, ensuring it was always pointing into the wall. For the central point, we divided the circle into 8 steps of 45°, to turn fully. Furthermore, the camera was pointed down for 25° to represent what participants might perceive more accurately. We automated this process and adjusted the lighting conditions in each room. An overview of the five measuring points with their respective rotations can be seen in Figure 12. We made sure that there was no statistical difference between the luminance in different rooms. In all rooms, we had a mean lux measurement of 30.1 ($std = 5.61$). We had no values of $p < 0.05$ when applying a two-tailed t-test over the lux measurements collected (see Table 4). Thus, luminance should not have a significant effect on our data.

Table 4: To ensure there was no difference in lighting for the different rooms, we did a two-tailed t-test between the recorded lux readings in all of the rooms. In this table, we report the p-values found when comparing the lux values of each room.

	Office	**Kitchen**	**Bath.**	**Bed.**	**Dining**	**Garage**	**Meeting**
Living R.	.761	.782	.577	.417	.644	.893	.179
Office		.952	.969	.907	.864	.702	.867
Kitchen			.964	.968	.862	.69	.941
Bathroom				.880	.741	.576	.798
Bedroom					.537	.614	.924
Dining R.						.796	.433
Garage							.501