

Quantifying the Effect of Visual Impairments on Daily Activities in Virtual, Interactive Environments

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Abstract

We propose a novel approach that utilizes virtual reality (VR) and simulation environments to quantify the impact of visual impairments (VIs) on daily tasks, e.g., to what extent does glaucoma slow people down in wiping a table or chopping vegetables? We utilize clinical data from patients to develop visual field models, allowing VR to mimic the visual perception of VI patients as if it is seen through their eyes. Additionally, we leverage BEHAVIOR, the state-of-the-art simulation environment, to recreate a household environment for six daily activities. By measuring the disparity between the subjects' performance with and without VI, we can accurately quantify the impact of VIs. We further quantify the effects of VIs on body and eye movements, and model how movement strategies affect task performance under the influence of VIs. We hope our results can provide valuable insights into the challenges faced by individuals with VIs.

Keywords: Visual Impairments; Virtual Reality; Natural Tasks

Introduction

Visual impairment (VI) affects at least 285 million individuals worldwide (Pascolini & Mariotti, 2012). Common VIs in the U.S. include myopia (affects 23.9% population), cataracts (17.1%), age-related macular degeneration (AMD, 2.1%), glaucoma (1.9%) (National Eye Institute, 2010), and presbyopia (83.0%+ for age 45+) (Berdahl et al., 2020). Although the effects of VI are diverse, they all play a role in diminishing one's ability to perform daily household activities, which detracts a patient's quality of life (Khorrami-Nejad, Sarabandi, Akbari, & Askarizadeh, 2016). Hence, quantifying the effect of VIs on household tasks is a first step towards understanding the extent to which VI impacts a patient's quality of life. In this work, we make the first attempt to quantify the effect of visual impairments on daily tasks in a realistic household simulator with virtual reality (VR). An overview of our experiment design can be seen in Fig. 1.

Our first contribution is a simulation platform with VR interface to study VIs in household activities. We focus on household tasks as people spend a significant amount of time on them (Stiglitz, Sen, Fitoussi, et al., 2009). Additionally, performing these activities efficiently is critical to a person's quality of life. We recreated a household environment in VR by leveraging a state-of-the-art simulator, BEHAVIOR (Benchmark for Everyday Household Activities in Virtual, Interactive, and Ecological Environments) (Srivastava et al., 2022; Li et al., 2022), which provides high-quality rendering effects and realistic physical interactions.

This platform overcomes several limitations of previous work. Firstly, self-reported questionnaires provide useful insight into the impact of VIs (N. Jones, Bartlett, & Cooke, 2019), but an accurate estimate requires data to be collected in a controlled study. Clinical trials can accurately measure the performance of VI patients but are limited to simple, isolated tasks in well-controlled laboratory settings.

Secondly, real-world studies (West et al., 2002; Aki, Atasavun, Turan, & Kayihan, 2007; Hallemans, Ortibus, Truijten, & Meire, 2011; Houwen, Visscher, Lemmink, & Hartman, 2008; Aki, Atasavun, & Kayihan, 2008; Wood & Troutbeck, 1994) are challenging; hence, tasks are restricted to locating objects in a room or reading street signs (Wei et al., 2012). Virtual simulation environments allow us to perform experiments in more complex tasks and settings while ensuring rigorous experimental control, such as lighting conditions and object placement. Additionally, VR mitigates the safety risks in interactive real-world experiments, such as tripping or crashing vehicles (Wood & Troutbeck, 1994).

At last, current VI studies that utilize VR are limited in their interactivity and realism in their simulations, restricting studies to non-interactive visual search (P. R. Jones, Somoskeöy, Chow-Wing-Bom, & Crabb, 2020; P. R. Jones & Ometto, 2018) or navigation (Pivik, McComas, MacFarlane, & Laflamme, 2002) tasks. For the purpose of developing robotic solutions, researchers in computer vision and robotics have created simulation environments with high visual and physical realism. The BEHAVIOR / iGibson 2.0 (Srivastava et al., 2022; Li et al., 2022, 2021) simulator is particularly suitable for our study since it is a household environment. With modern computer graphics and physical simulation technologies, BEHAVIOR allows us to study complex and interactive tasks that are not possible before, such as wiping a table or slicing vegetables.

Our second contribution is an implementation of VR rendering models of five common VIs, each with three stages. We develop visual field models utilizing clinical data from patients for the five aforementioned common VI types. With the visual field models and the use of VR, we could accurately render the stimulus, exactly as if it is seen through the view of a VI patient's eyes.

Conducting a study by simulating VIs with healthy subjects instead of patients allows for precise control of the severity of VIs. Doing so isolates the impact of visual impairment

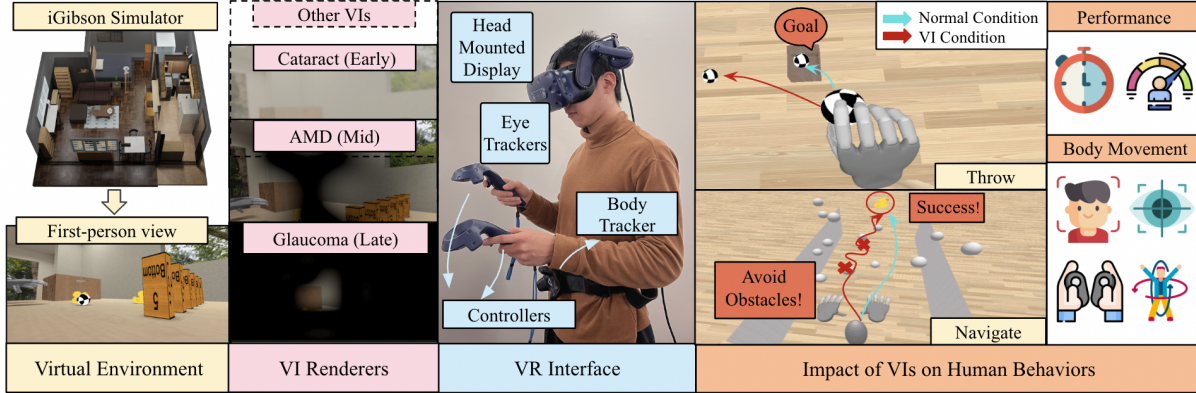


Figure 1: An overview of the experimental design.

from other common coexisting motor or cognitive disabilities (Zheng et al., 2018; Wagner, Haibach, & Lieberman, 2013), especially in older adults (McLean, Guthrie, Mercer, Smith, et al., 2014). Compared to VI simulation devices such as goggles (Wood & Troutbeck, 1994; Zagar & Baggary, 2010), VR simulation is more powerful and supports more VI types. This approach is made possible with the use of visual field models from clinical studies across various stages of VIs. These models, when combined with VR, can be precisely chosen to emulate the exact same type of VI and the exact magnitude of VI severity for all subjects.

The new technology platform and methodology allow us to accurately quantify the impact of VIs on daily household tasks. By collecting human performance and movement data, including success rate, time, as well as body and eye movements, we can accurately quantify and examine the strategies used by people with VI to overcome difficulties in completing household tasks. We hypothesize that the effect of VIs will be task-dependent, and severe cataracts, AMD, and glaucoma will significantly reduce performance in most of the tasks. We hypothesize that our findings can be generalized to the real-world environment, and we will validate this by setting up an identical task in the real-world. At last, previous work has shown that one can use VR to promote empathy toward people with disabilities (Wilding et al., 2022); we will investigate whether our study yields a similar effect.

Method

An overview of our experiment design can be seen in Fig. 1. To create a fully interactive virtual environment, we use the BEHAVIOR/iGibson 2.0 simulator (Li et al., 2021; Srivastava et al., 2022). We then develop VI renderers from VI patients’ visual field models to render virtual environments. Then, we measure human performance in six tasks and quantify the effect of VIs by comparing the performance in the normal condition with VI conditions.

Tasks

Being able to perform household activities efficiently is important for the quality of life. We use the BEHAVIOR simulator (Srivastava et al., 2022) which contains 100 daily house-

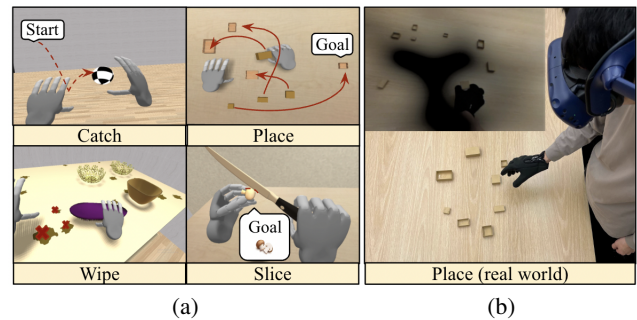


Figure 2: (a) Our experiment includes six tasks that capture the visuomotor skills needed for household activities. Two other tasks (throw and navigate) are shown in Fig. 1. (b) For Place, we create a real-world version to validate the use of VR and simulation.

hold activities from the American Time Use Survey and identified visuomotor skills that are important for performing these activities. Based on these skills, we design the following six tasks (Fig. 2a):

1. **Catch:** A Subject stands in an open space facing a wall. A tennis-sized ball is launched from the wall and bounces once on the ground, and the subject needs to catch it with his/her dominant hand (Diaz, Cooper, Rothkopf, & Hayhoe, 2013). The launching position of the ball slightly differs across trials.
2. **Throw:** A subject stands still in front of a basket that moves left and right at a constant speed. The subject needs to throw the ball into the basket. The starting position of the basket and its moving speed slightly differ across trials.
3. **Place:** A subject stands in front of a table with four pairs of boxes and blocks of different sizes and shapes. The subject needs to place each block into its matching box. The starting positions of the boxes and blocks are randomized.
4. **Slice:** A subject stands in front of a kitchen counter. The subject needs to pick up a knife, align it with a mushroom, and slice the mushroom in half.
5. **Wipe:** A subject stands in front of a dirty dinner table with three tableware on top. The subject needs to wipe off the

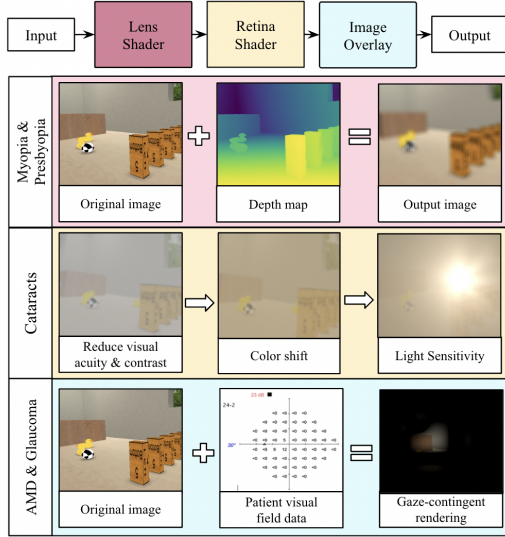


Figure 3: Visual impairment simulation pipeline. Myopia and presbyopia are simulated by changing the lens shader and cataracts by changing the retina shader, while AMD and glaucoma are simulated using the image overlay mechanism.

stains without colliding with the tableware. The positions of the stains and tableware are randomized between trials.

6. **Navigate:** A subject starts at one end of a hallway and walks to reach a target object on the other end. There are 15 moving obstacles between the subject and the target. The starting positions of the obstacles are randomized.

These tasks involve a diverse set of perceptual abilities, e.g., depth, shape, size, spatial, and motion perception. They also require fine visuomotor skills such as aiming, throwing, as well as intercepting or avoiding dynamic objects. We hypothesize that these abilities and skills are likely to be affected by the five common VIs.

Visual Impairment Renderers

Inspired by the Visual System Simulator (Schulz et al., 2019), we use post-processing shaders based on OpenGL to simulate VI effects. We constructed two shaders to simulate how light passes through the lens and retina of the human eyes respectively (Fig. 3). The lens shader simulates refraction, followed by the retina shader which simulates various forms of retinopathy. On top of the shaders, we use iGibson’s image overlay mechanism (Li et al., 2021) to simulate visual field loss. We include five common VIs using this pipeline. Each VI has three levels: early, mid, and late, based on the grading system provided by medical research and reports.

Myopia & presbyopia affect the trajectory of light refracted onto the retinal plane. We simulate these two VIs in the lens shader based on the concept of depth of field in photography. The simulation procedure is shown in Algorithm. 1, inspired by the previous work (Schulz et al., 2019). For presbyopia, we use 1.35D, 2.15D, and 2.90D for three stages (Seidu, Bekibele, & Ayorinde, 2016). For myopia, we use -3D, -6D, -9D (Cline, Hofstetter, & Griffin, 1980).

Algorithm 1 Myopia and Presbyopia Simulation

Require: Input image I , depth map Z , diopters D

- 1: **for** each pixel $i \in I$ **do**
 - 2: Cast a light ray from i towards the retinal plane through a normal lens
 - 3: Obtain the intersection point p on the plane
 - 4: Retrieve depth z_i of i from Z
 - 5: Compute the focal length as the distance from i to the lens with z_i , and change it according to D
 - 6: Cast 17 rays from p towards I , each of which slightly differs in their orientations
 - 7: Obtain the 17 pixels at which they intersect I
 - 8: Average these pixel values to get the new value for i
 - 9: **end for**
-

Cataracts are cloudy areas in the lens of the eye. We choose the most common form of cataracts, nuclear cataracts, and their three-stage grading standard (Thylefors et al., 2002). Inspired by CatARact (Krösl et al., 2020), we simulate cataracts by modifying the retina shader, as follow (Fig. 3):

1. **Reduce visual acuity:** we apply Gaussian blur to the input image to simulate blurry vision caused by cataracts.
2. **Reduce contrast:** we interpolate between the input image and a grey image to simulate faded colors using the following equation: $\text{output} = (1 - c) \cdot \text{input_image} + c \cdot \text{grey_image}$, where c is the contrast reduction factor that varies across different cataracts stages (0.2, 0.45, 0.7). The pixel value of the grey image is (0.5, 0.5, 0.5).
3. **Color shifting:** we interpolate between the input image and a fixed, single-color image to simulate color shift: $\text{output} = (1 - t) \cdot \text{input_image} + t \cdot \text{shift_image}$, where t is the color-shifting factor, which varies across different cataracts stages (0.05, 0.125, 0.2). The pixel value of the shift_image is set to be (0.8, 0.5, 0.0).
4. **Light sensitivity:** Sensitivity to light is increased due to the effects of light diffraction caused by cataracts. We model this with OpenGL’s lens flare algorithm (Woo, Neider, Davis, & Shreiner, 1999) to simulate an artificial flare at the center of the visual field (Häkkinä, Colley, Väyrynen, & Yliharju, 2018).

AMD & glaucoma AMD and glaucoma cause visual field loss in the central and peripheral visual field, respectively. We simulate three stages of AMD (Acton, Gibson, & Cubbidge, 2012), and three stages of glaucoma according to the standard criteria from Hodapp, Parrish, and Anderson (1993).

Inspired by OpenVisSim (P. R. Jones et al., 2020), we use actual patients’ visual field data from static automated perimetry (SAP) Humphrey visual field test (Acton et al., 2012; Susanna Jr & Vessani, 2009; Bengtsson & Heijl, 2008; Leleu et al., 2019), see Fig. 3. We create a mask based on the data and overlay the mask onto the input image to simulate the effect of visual field loss. The masks are gaze-contingent; hence, we use eye trackers to obtain eye movement data while running experiments.

Hardware setup We used HTC Vive Pro Eye for VR, which has in-built eye and body trackers (Fig. 1). While we mainly focus on the visual stimulus, to simulate touch sensation which is important for interacting with objects, we implemented haptic feedback (using vibration) to simulate collisions between the subject’s virtual hands and body with other objects. To ensure that the simulation and rendering speed are above 60Hz, the experiment is run on a PC with AMD Ryzen Threaddripper 3960x, dual Nvidia RTX 3090 graphics cards, and 128GB RAM. The PC operates on Windows 10 with SteamVR and SRanipal installed.

Experiments

Ten subjects were recruited for the study. Their demographic information including gender, age, current visual impairment, and dominant hand was collected. All subjects (5 male, 5 female, mean age = 26, min age = 22, max age = 29) have normal or corrected vision.

Before the experiment, subjects were equipped with the body tracker and head-mounted display, and taught to use the hand controllers. Then, eye trackers were calibrated for each subject. Each of the six tasks started with a practice session. The subjects were given verbal instructions on how to complete the tasks. Then, a practice session was conducted until they can reliably achieve success in each task, i.e., 70% success rate in *Catch*, or a certain number of successful attempts in the other tasks. This practice session was performed to eliminate potential variation in performance that stems from learning and familiarization.

Then, subjects were instructed to complete the six tasks under the five VI conditions. The order of the conditions was counterbalanced to further account for the effect of familiarization. Each condition contains a different number of repeated trials (2-10) for different tasks.

During the experiment, we recorded dependent variables that are helpful metrics to quantify human performance and efficiency. Performance metrics include task failure rate, task completion time, collision time, and object displacement. The efficiency metrics include human head, body, and hands translation and rotation, eye movement distance, eye fixation count and time, as well as pupil dilation. Once all 16 conditions (15 VI conditions and 1 normal) of a task were finished, subjects provided ratings for each condition on their perceived difficulty, and took a 5-minute break before the next task. We have collected a total of 14 hours of data in VR.

Real-world study An underlying assumption is that for the tasks and visuomotor skills in our study, the main results found using simulation and VR can be generalized to real-world settings. This study aims at validating this assumption.

Place is a task we can study in the real world. It is difficult to conduct experiments with the other five tasks – this again demonstrates the benefits of using simulation. We 3D-printed the four pairs of boxes and blocks so they are the same shape, size, and color to accurately represent the dimensions of objects in the simulation (Fig. 2b).

The Vive head-mounted display has two front-facing cameras that allow us to display the real-world environment to the subjects in real-time. We can simulate AMD and glaucoma by overlaying the masks directly onto real-world images. To minimize the effect of tactile sensing, the subjects wear a glove during the experiment. Each subject performed three trials in each condition (normal, three stages of AMD, and three stages of glaucoma). We recorded the task completion time of each trial which will be used to compare against the data obtained in the simulation. We have collected 2 hours of human data in this real-world setting.

Empathy survey Previous work has shown that VR can be used to foster empathy towards people with disability (Wilding et al., 2022). We constructed a 22-question survey from three previous surveys (Spreng*, McKinnon*, Mar, & Levine, 2009; Yucker et al., 1970; Bell & Silverman, 2011) to measure empathy and attitude toward VI patients. The subjects were asked to complete the questionnaire before and after the experiment.

Results

Supplemental materials including video demos recorded in VR, additional experiment details, data analyses, and result figures can be found on our anonymized website¹.

Effect of VIs on Task Performance

We first chose a main performance metric for each task: failure rate (total misses over the total attempts) for *Catch* and *Throw*, task completion time for *Place*, *Slice*, and *Wipe*, and obstacle collision time ratio for *Navigate*. All these metrics strongly correlate with the subjects’ ratings on task difficulties under different VI conditions (average Pearson’s $r = .92$ and $p < .05$ for all).

Catch We found that late-stage cataracts ($t(10) = 4.45, p < .01; d = 1.87$), mid- ($t(10) = 4.81, p < .01; d = 2.03$) and late-stage ($t(10) = 9.49, p < .01; d = 3.38$) AMD, mid- ($t(10) = 4.84, p < .01; d = 1.60$) and late-stage ($t(10) = 12.83, p < .01; d = 5.64$) glaucoma, and early-stage presbyopia ($t(10) = 2.45, p < .05; d = 0.29$) lead to a significant increase in failure rate compared to the control.

Throw We found that late-stage cataracts ($t(10) = 3.88, p < .01; d = 0.69$), mid- ($t(10) = 2.76, p < .05; d = 0.75$) and late-stage ($t(10) = 2.75, p < .05; d = 1.05$) AMD, late-stage glaucoma ($t(10) = 6.62, p < .01; d = 2.33$), and late-stage myopia ($t(10) = 2.53, p < .05; d = 0.91$) show a significant increase in failure rate compared to the control. Notably, in late-stage AMD ($M = 4.31, SD = 1.16$) and glaucoma ($M = 5.73, SD = 1.73$), subjects spend significantly more time compared to normal ($M = 3.43, SD = 1.01$), ($t(10) = 3.25, p < .05; d = 0.77; t(10) = 4.6, p < .05; d = 1.54$), but this does not reduce the failure count.

Place We found that late-stage cataracts ($t(10) = 4.39, p < .01; d = 1.84$), mid- ($t(10) = 2.48, p < .05; d = 0.68$) and late-stage ($t(10) = 27.63, p < .01; d = 10.37$)

¹<https://sites.google.com/view/vi-vr/>

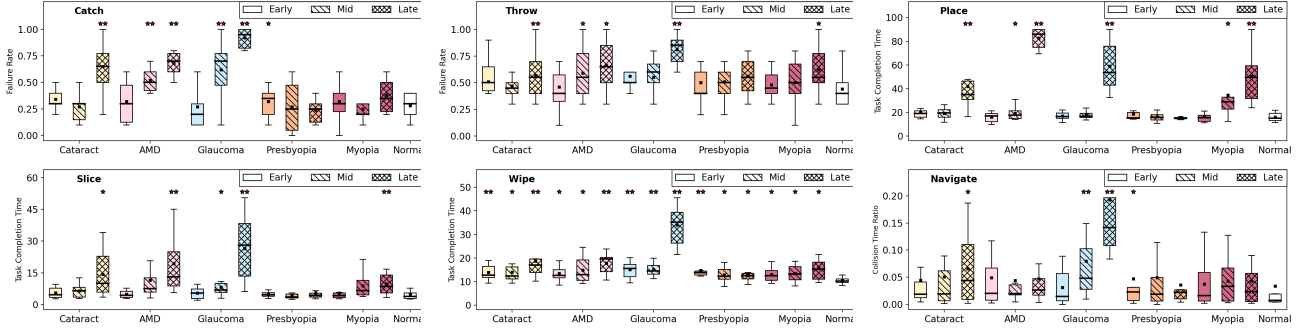


Figure 4: Box plot of the median and interquartile range of main performance metrics in six tasks. *and**: Significant difference from the normal condition at $p < .05$ and $p < .01$.

AMD, late-stage glaucoma ($t(10) = 6.84, p < .01; d = 2.90$), and mid- ($t(10) = 2.95, p < .05; d = 1.20$) and late-stage ($t(10) = 5.43, p < .01; d = 2.22$) myopia show a significant increase in task completion time compared to the control.

Slice We found that late-stage cataracts ($t(10) = 2.98, p < .05; d = 1.19$), late-stage AMD ($t(10) = 3.53, p < .01; d = 1.42$), mid- ($t(10) = 2.83, p < .05; d = 0.93$) and late-stage ($t(10) = 5.04, p < .01; d = 2.01$) glaucoma, and late-stage myopia ($t(10) = 3.47, p < .01; d = 1.29$) show a significant increase in task completion time.

Wipe We found that all VIs, including early- ($t(10) = 3.79, p < .01; d = 1.38$), mid- ($t(10) = 2.40, p < .05; d = 1.04$), and late-stage ($t(10) = 4.07, p < .01; d = 1.63$) cataracts, early- ($t(10) = 2.68, p < .05; d = 1.19$), mid- ($t(10) = 2.51, p < .05; d = 1.09$), and late-stage ($t(10) = 5.89, p < .01; d = 2.08$) AMD, early- ($t(10) = 3.96, p < .01; d = 1.69$), mid- ($t(10) = 4.53, p < .01; d = 2.01$), and late-stage ($t(10) = 9.75, p < .01; d = 3.89$) glaucoma, early- ($t(10) = 3.79, p < .05; d = 1.33$), mid- ($t(10) = 2.95, p < .05; d = 0.97$), and late-stage ($t(10) = 2.69, p < .05; d = 0.98$) presbyopia, and early- ($t(10) = 2.59, p < .05; d = 1.06$), mid- ($t(10) = 3.21, p < .05; d = 1.14$), and late-stage ($t(10) = 2.62, p < .05; d = 1.18$) myopia show a significant increase in task completion time compared to the control. Notably, late-stage glaucoma ($M = 18.28, SD = 7.28$) leads to a significantly higher total number of collisions with irrelevant objects compared to normal ($M = 11.14, SD = 4.32$), $t(10) = 4.33, p < .05; d = 1.13$.

Navigate We found that late-stage ($t(10) = 2.41, p < .05; d = 0.54$) cataracts, mid- ($t(10) = 3.25, p < .01; d = 0.66$) and late-stage ($t(10) = 4.38, p < .01; d = 1.57$) glaucoma, and early-stage presbyopia ($t(10) = 2.73, p < .05; d = 0.23$) show a significant increase in the collision time ratio compared to the control.

Remarks Late-stage glaucoma and cataracts reduce task performance significantly across all six tasks; this is followed by late-stage AMD (five tasks), late-stage myopia, mid-stage glaucoma, and mid-stage AMD (four tasks each). Out of all the VI conditions, late-stage glaucoma has the largest effect size. On average, it causes task performance

Table 1: Most frequent strategy adopted by the subjects to cope with VIs in different tasks.

Task	Catch	Throw	Place	Slice	Wipe	Navigate
Metrics (velocity)	body rotation	eye movement	right hand translation	right hand rotation	body translation	eye movement
Effect	↑	↓	↓	↓	↓	↓

to be $6.53\times$ worse than normal; this is followed by late-stage AMD ($3.27\times$) and late-stage cataracts ($2.89\times$), then mid-stage glaucoma, mid-stage AMD, and late-stage myopia (more than $2\times$).

Effect of Movement on Task Performance

The above results provide quantifiable evidence of the effect of VIs on task performance. To gain a deeper understanding of their relationship, our study utilizes two forms of analysis: the first focused on quantifying the impact of VIs on body and eye movements, while the second aimed to model how the body and eye movements affect task performance. Our study selected nine key metrics: eye movement velocity and the average translation/rotation velocity of the head, body, and both hands.

Body and eye movements under different VI conditions

We first analyze the impact of different VIs on subjects' body and eye movements. This analysis serves to provide insight into the coping strategies employed by individuals to complete tasks under VI conditions. Our results reveal that VIs have a substantial impact on eye movements, with 25 out of 90 conditions ($15\text{ VIs} \times 6\text{ tasks}$) resulting in a significant reduction in eye movement speed. Additionally, we observed that the translation velocity and rotation velocity of the right hand (the dominant hand for all subjects) were significantly slower in 18 and 17 conditions, respectively. However, it is important to note that the changes in movement metrics are task-dependent, as shown in Table 1. For instance, the most frequently used strategy is to increase body rotation velocity in Catch. A comprehensive table of the impact of all VI conditions on movement metrics in all tasks can be found in the supplemental materials on our website.

Body and eye movements and performance drop We performed multiple ordinary least square (OLS) regression to analyze the relationship between performance drop and move-

ment metrics. The regression model is $Y = \beta X + b$. Y is the performance drop (compared to normal) of a trial, and X includes the nine aforementioned movement metrics of that trial. These metrics are divided by the mean velocities under the normal condition. We then performed two analyses: aggregating the data across VIs to obtain a model for each task and aggregating the data across tasks to obtain a model for each VI condition.

Our first contribution provides insight into task-specific reasons for performance decrements. Our results demonstrate that the higher failure rate during the task of *Catch* is associated with increased body rotation and right hand translation velocities; in *Throw*, the performance decrement is correlated with elevated head translation velocity, right hand rotation velocity (faster wrist movements), and reduced head rotation and right hand translation velocities; in *Slice*, we observed a longer completion time, which was associated with elevated eye movement velocity, right hand translation velocity, left hand rotation velocity, and decreased right hand rotation velocity; *Wipe* showed a performance drop associated with decreased right hand translation and eye movement velocities; finally, the task of *Navigate* demonstrated a performance drop related to reduced body translation velocity.

The second sheds light on the performance decrements associated with VI across various tasks. Our findings indicate that a significant reduction in performance in late-stage glaucoma is correlated with decreased body translation velocity and elevated head translation velocity during the task of *Navigate*. However, we did not observe any consistent trends across other types of visual impairments. The large variance between tasks in results is primarily due to the task-dependent nature of the performance drops, i.e., the correlation between performance decrements and movement metrics varies across tasks. Further information regarding the results can be found in the supplemental materials on our website.

Real-world Study Results

As shown in Fig. 5, the increase in task completion time caused by AMD and glaucoma show similar patterns in the real world and in simulation. Although it is difficult to validate the other five tasks in the real world, this result provides preliminary evidence that our findings can be generalized to real-world settings in the chosen tasks.

Empathy Study Results

After the experiment, subjects' positive attitude or empathy scores show increasing trends in 17 out of 22 survey items. The increase is statistically significant for the item "*visually impaired people's misfortunes do not disturb me a great deal*" ($t(10) = 2.51, p < .05$, one-tailed), which indicates that subjects showed increased empathy towards the VI patients after the experiment.

Discussion

In this study, we quantify the impact of five distinct visual impairment conditions on daily tasks with a realistic house-

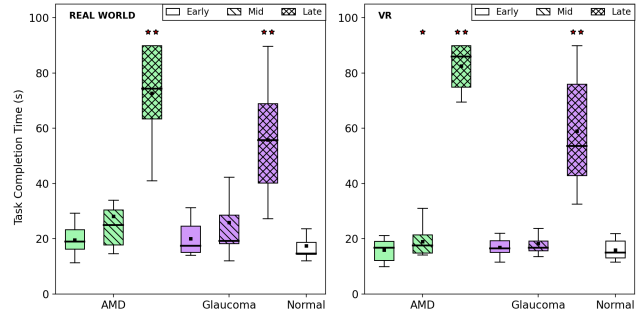


Figure 5: Our simulation and real-world studies show similar performance drop patterns in task *Place*.

hold simulator in virtual reality. We confirm our hypothesis that the effects of VIs are contingent upon the task being performed. Additionally, we further show that the strategies to cope with VI conditions are task-specific; this includes strategies involving body and eye movements that are potentially associated with performance drops.

Our study has found that late-stage cataracts, AMD, and glaucoma have a significant impact on the performance of individuals in most daily household tasks. This is consistent with previous research which has shown that individuals with severe visual field loss report decreased scores on mobility and self-care categories in quality-of-life questionnaires (Khorrami-Nejad et al., 2016). Our findings on glaucoma are also in line with prior work that shows that the condition leads to a severe reduction in stereopsis (Gupta, Krishnadev, Hamstra, & Yücel, 2006). This is consistent with the results of our study, as all of the tasks we evaluated heavily rely on depth perception.

Previous work (Van der Stigchel et al., 2013) shows that there is an increase in the number of eye movements necessary to locate targets in search tasks in MD patients compared to the control group; however, these experiments involved a static chin rest where the subject's head and pose is at a set distance from the screen. Our unrestricted experimental setup enables flexibility in subjects' body, head, hands, and eye movements which allows us to observe a larger variety of strategies used in performing natural tasks.

It is worth noticing that due to the limitation of VR technology, simulated VIs are different from real VIs in a number of important ways. For example, patients can utilize tactile and auditory information in the real world to compensate for the VIs. Comparing data from simulated VIs with data from people with actual VIs would help us better understand the differences.

In an effort to advance future research in this area, we are making our VI simulation algorithms, virtual environment, task designs, VR interface, and data collection tools open-source. Our aim is to inspire further investigation into the correlation between visual impairments and quality of life, as well as the relationship between visual perception and behavior in everyday tasks.

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