Identifying Behavioral Correlates to Visual Discomfort

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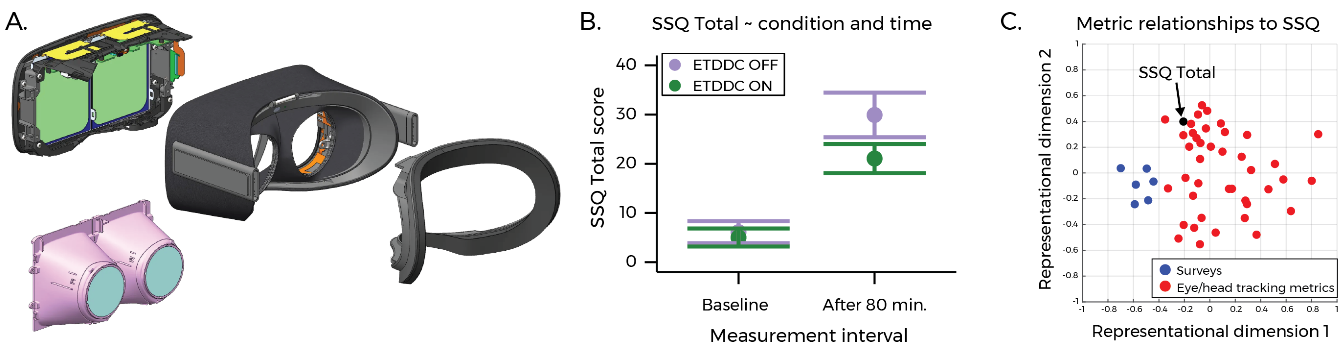

Fig. 1. In this study we evaluate visual discomfort in virtual reality using a naturalistic, within-subjects paradigm. We find that optical distortions from near-eye optics (pupil swim) increase visual discomfort, and eye-tracked dynamic distortion correction (ETDDC) can mitigate that discomfort. We use representational similarity analysis to identify changes in blink and eye movement behavior as potential indicators of visual discomfort among 41 head and gaze metrics collected during our study. (A) We modified an Oculus Rift with custom high pupil swim optics and implemented eye-tracked dynamic distortion correction to enable our user study. Participants played Job Simulator for 80 minutes with and without ETDDC enabled. (B) At session completion, SSQ Total was reduced when ETDDC was enabled, indicating visually induced motion sickness symptom severity was moderated by pupil swim. Markers represent average SSQ Total and error bars are standard error of the mean. (C) Using multidimensional scaling, we find that some head and gaze metrics are more similar to SSQ Total than abbreviated surveys used in place of SSQ during the experiment (Misery Scale and CVS-Q).

Outside of self-report surveys, there are no proven, reliable methods to quantify visual discomfort or visually induced motion sickness symptoms when using head-mounted displays. While valuable tools, self-report surveys suffer from potential biases and low sensitivity due to variability in how respondents may assess and report their experience. Consequently, extreme visual-vestibular conflicts are generally used to induce discomfort symptoms large enough to measure reliably with surveys (e.g., stationary participants riding virtual roller coasters). An emerging area of research is the prediction of discomfort survey results from physiological and behavioral markers. However, the signals derived from experimental paradigms that are explicitly designed to be uncomfortable may not generalize to more naturalistic experiences where comfort is prioritized. In this work we introduce a custom VR headset designed to introduce significant near-eye optical distortion (i.e., pupil swim) to induce visual discomfort during more typical VR experiences. We evaluate visual comfort in our headset while users play the popular VR title Job Simulator and show that eye-tracked dynamic distortion correction improves visual comfort in a multi-session, within-subjects user study. We additionally use representational similarity analysis to highlight changes in head and gaze behavior that are potentially more sensitive to visual discomfort than surveys.

CCS Concepts: • **Computing methodologies** → *Virtual reality*; • **Human-centered computing** → **User studies**.

Additional Key Words and Phrases: pupil swim, dynamic distortion correction, ETDDC, visually-induced motion sickness, VIMS, visual discomfort, oscillopsia

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1 Introduction

Understanding visually induced motion sickness (VIMS) and visual discomfort experienced while using head-mounted displays (HMDs) is among the most challenging perceptual problems in virtual reality (VR). Measuring and characterizing VIMS alone is a significant effort; the current gold standard is to use standardized surveys such as the Simulator Sickness Questionnaire (SSQ) [Kennedy et al. 1993]. Due to the low sensitivity and specificity of self-reported surveys, researchers often resort to extreme measures to induce visual discomfort through the introduction of large visual-vestibular conflicts (VVCs) in short amounts of time [LaViola Jr 2000]. This is generally achieved by showing stationary participants virtual camera motion, for example, by riding virtual roller coasters [Chang et al. 2021; Islam et al. 2021]. Such studies are typically completed in 10-30 minutes and, when attempting to test multiple conditions, either utilize between-subjects designs or run multiple conditions within the same session for within-subjects designs [Luong et al. 2022]. These study designs complicate the proper identification of factors that contribute to VIMS by increasing noise and introducing additional confounds (e.g., running multiple conditions together conflates condition and time).

Three general classes of studies have emerged that are broadly based on the experimental design outlined above: (i) studies that relate demographic information (e.g., age, interpupilary distance, gender, etc.) to VIMS susceptibility [Arns and Cerney 2005; Bannigan et al. 2024; Rebenitsch and Owen 2014], (ii) studies that attempt to identify behavioral changes (e.g., head and gaze dynamics) that can be used in place of surveys [Jasper et al. 2020; Martin et al. 2020; Wibirama et al. 2020], and (iii) a relatively new class of studies that aim to model and predict the magnitude of VIMS symptoms based on a combination of behavioral, demographic, and visual information using classes of models ranging from linear regression to neural networks [Chang et al. 2021; Hell and Argyriou 2018; Islam et al. 2021; Luong et al. 2022; Wen et al. 2024; Zhao et al. 2023].

The latter two categories of studies aim to address the limitations of survey-based data collection by supplementing survey responses with additional signals for VIMS characterization. However, an open question in interpreting data derived from paradigms reliant on camera-motion based VVCs is whether the trends identified in these atypical settings generalize to more naturalistic use cases. Head and gaze behavior are highly task-dependent [Burlingham et al. 2024; Malpica et al. 2023], and changes in their characteristics derived from a paradigm intended to quickly induce VIMS may not apply to more typical scenarios (e.g., immersive gaming designed with visual comfort in mind). Such experiences avoid large VVCs and usually involve task-driven interaction rather than free-gaze explorations employed in many lab-based studies.

Additionally, many comfort mitigation strategies are designed specifically to reduce discomfort arising from differences in camera and user motion [Fernandes and Feiner 2016; Hu et al. 2019; Serrano et al. 2020; Tariq and Didyk 2024; Xiao and Benko 2016]. Many applications attempt to avoid this problem altogether by replacing smooth locomotion with teleportation mechanics or building experiences that do not require significant user translation at all (e.g., Beat Saber). Despite these efforts, VIMS remains a problem for some VR users because a number of VVCs are still present in modern-day HMD hardware. For example, tracking errors and motion-to-photon latency [Palmisano et al. 2020], inaccurate render camera placement [Guan et al. 2023; Krajancich et al. 2020], and gaze-contingent optical distortions from near-eye optics (i.e., pupil swim) [Geng et al. 2018] can all contribute to geometric inconsistencies between images seen by the user and the perspective-correct images of the virtual environment consistent with the user's head and eye movements. Other limitations in HMD hardware can introduce other non-geometric errors that lead to visual discomfort, including vergence-accommodation conflicts [Hoffman et al. 2008] and physical discomfort from the size and weight of the headset.

The design of VR HMD optics presents a particularly interesting tradeoff for VIMS. Smaller and more compact optics and displays enable smaller, more ergonomic headsets but can often lead to more pupil swim. It has been speculated, but not conclusively shown, that the VVC introduced by pupil swim can lead to visual discomfort. In this work, we experimentally manipulate pupil swim and assess its impact on visual comfort. In doing so we avoid the need for camera-based VVC to induce discomfort and make the following specific contributions:

- We retrofit an Oculus Rift with high pupil swim optics and implement eye-tracked dynamic distortion correction (ETDDC) in a custom OpenXR implementation that allows the use of our headset with all Meta PC VR content. We enable or disable ETDDC to manipulate pupil swim magnitude and study the impact of pupil swim on VIMS.
- We present the longest and most naturalistic study on visual discomfort to date, with users playing Job Simulator for 80 minutes in two separate sessions in a within-subjects experiment (all participants complete all conditions).
- We use standardized surveys to evaluate visual comfort and show, for the first time, that pupil swim leads to increased visual discomfort through the use of ETDDC to improve comfort in our 80-minute sessions.
- We use representational similarity analysis (RSA) as a tool to investigate visual discomfort and identify potential behavioral markers that can more accurately and quickly indicate the onset of discomfort compared to surveys.

2 Related Work

Visual Discomfort in VR. It is commonly accepted that a subset of potential users within the general population are likely to experience some degree of VIMS or visual discomfort resulting from VR use [Keshavarz et al. 2023; Stanney et al. 2003]. A leading hypothesis about the cause of VIMS during VR use is that the presence of VVC leads to elevated discomfort symptoms [Bos et al. 2008; Oman 1990]. According to this framework, an inter-related set of features of the hardware and software that compose modern VR experiences may exaggerate VVC, including but not limited to, field of view

[Harvey and Howarth 2007; Lin et al. 2002], fixed virtual image distance [Shibata et al. 2011], and motion to photon latency [DiZio and Lackner 2000; Palmisano et al. 2019]. Many studies also attribute VIMS to VVCs that lead to self-motion illusions arising from visual input that is inconsistent with vestibular stimulation [Bonato et al. 2008; Keshavarz and Hecht 2011; Keshavarz et al. 2019, 2015].

Demographic Correlates to Discomfort. Subsets of users could be more or less likely to experience VIMS based on a variety of characteristics that may intersect with hardware/software causes, including susceptibility based on prior experience of VIMS [Golding et al. 2021; Häkkinen et al. 2006; Oh and Son 2022; Rebenitsch and Owen 2014; Stanney et al. 2003], age [Arns and Cerney 2005; Hakkinen et al. 2002], and gender or sex [Bannigan et al. 2024; Stanney et al. 2003; Weech et al. 2020] (although gender/sex differences may be a result of differences like average interpupillary distance [Stanney et al. 2020]). We refer the reader to Luong et al. [2022] for an in-depth review of the most relevant works studying these demographic correlates to VIMS. While certain demographic characteristics may be correlated with VIMS, they cannot be directly influenced or controlled to mitigate potential discomfort. Our study shows that large amounts of pupil swim can induce VIMS and, in doing so, provides actionable evidence for potential VIMS mitigation in hardware design.

Behavioral Correlates to Discomfort. Finding behavioral correlates of VIMS to use in place of self-report surveys has been an active research area for decades [Saredakis et al. 2020]. Many metrics have been studied including physiological responses [Dennison et al. 2016; Kim et al. 2005; Martin et al. 2020], postural stability [Jasper et al. 2020; Yokota et al. 2005], and eye movements [Webb and Griffin 2003]. Some works have found the impact of different metrics, including visual yaw rotation [Nooij et al. 2017], retinal slip velocity [Yang et al. 2011], blink rate [Abusharha 2017], fixations [Chang et al. 2021; Wibirama and Hamamoto 2014; Wibirama et al. 2020], or saccades and visual-vestibular reflexes [Neupane et al. 2018; Nooij et al. 2017]. Furthermore, some works have built predictive models of discomfort leveraging the combination of both demographics and eye-related measurements [Chang et al. 2021; Islam et al. 2021; Luong et al. 2022].

Notably, a vast majority of work used to develop our understanding of VIMS during VR use is predicated upon short-duration, high VVC visual stimuli, without a "no conflict" baseline or repeated measures study design to compare relative changes in SSQ ratings. A recent meta-analysis found that 67.3% (37/55) of studies evaluating VIMS included sessions that lasted <20 minutes and 90.9% (50/55) lasted <30 minutes [Saredakis et al. 2020]. Even within these short time frames, studies will often attempt to measure VIMS sensitivity to multiple factors, which means that many conclusions about mechanisms that lead to VIMS are effectively extrapolated from very short-term exposures of several minutes with measurements that are potentially affected by high VVC visual input seen minutes before and/or the natural increase of discomfort scores over time from any headset use. We attempt to address many of these issues in our study design with a multi-session, within-subjects long duration VIMS evaluation conducted with naturalistic behavior where the only factor changed between sessions is the use of ETDDC.

VIMS from Pupil Swim in HMDs. Chan et al. [2022] have run the lone study to explicitly examine the relationship between pupil swim and VIMS and report that user estimates of VIMS vary with the magnitude of pupil swim across four lens designs. However, their results cannot conclusively link pupil swim and VIMS as they studied 92 conditions in one continuous session and asked participants to predict their VIMS symptoms 20 minutes in the future after viewing each condition for one minute. McLean et al. [2023] built custom minifying spectacles, and demonstrated that differences in magnification (from combinations of 0%, 2%, and 4%) between the two eyes lead to increased visual discomfort over one to two hours while performing real-world tasks. While these glasses were designed to induce a global minification and produce a significantly different type of optical distortion than what is observed with pupil swim, this study does demonstrate that optical distortions can lead to increased discomfort.

Representational Similarity Analysis. RSA is a method first made popular in cognitive neuroscience that uses similarity as a metric between pairwise entities to construct a representational map or geometry among all possible entities of interest [Kriegeskorte et al. 2008a]. In the context of eye tracking or physiological signals, these entities could be different types of eye movements, physiological signals, or motion sickness self-report surveys. The similarity metric used can be determined by the correlation between the entities, the Euclidean distance, or through cross-validated decoding performance in distinguishing between two entities to construct Representational Dissimilarity Matrices (RDMs). This process allows all entities to exist within representational space, removing the limitations of the original measurements used to measure that entity. RSA has been employed as a framework for hypothesis testing [Carlson et al. 2013; Cecere et al. 2017; Cichy et al. 2014; Giordano et al. 2013; Kriegeskorte et al. 2008a], and for comparing between model systems [Khaligh-Razavi and Kriegeskorte 2014; Kriegeskorte et al. 2008b; Tovar et al. 2020; Xu and Vaziri-Pashkam 2021] due to its flexibility. Recent work has used RDM feature re-weighting to optimize and identify links between model and target RDMs [Hendrickson et al. 2024; Kaniuth and Hebart 2022]. In this study, we apply RSA to identify behavioral correlates to self-reported VIMS, providing a novel application of this method in VIMS research.

3 Hardware and Software

The optical designs and distortion correction meshes used to minimize pupil swim in commercially available HMDs are not readily available to developers–a significant hurdle for aftermarket ETDDC implementation. It is possible to measure the distortion correction mesh directly by removing the optics and imaging a known pattern on the display and to additionally characterize the viewing optics by building calibration rigs to measure distortion throughout the eye box [Martschinke et al. 2019]. We elected instead to replace the lenses of an Oculus Rift with an off-the-shelf optic which allows us to use a published design to generate distortion correction meshes for ETDDC. We then implement our own distortion correction software for both static and eye-tracked distortion correction with a Light Field Portal distortion representation [Guan et al. 2022].

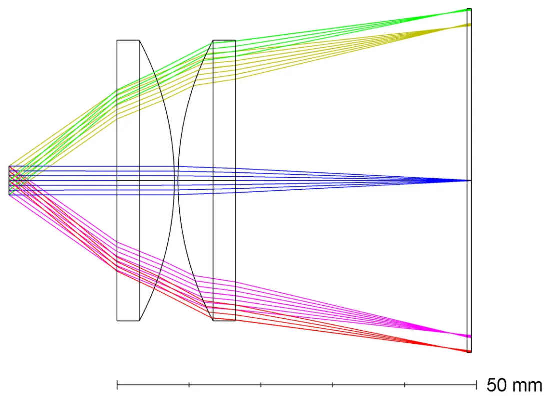

Fig. 2. Hourglass optical design in modified Rift headset designed to introduce large changes in gaze-contingent optical distortion (i.e., pupil swim).

3.1 Optical Design

When generating our optical design, we aimed to increase the amount of pupil swim in the HMD to induce a larger VVC so any potential visual discomfort could be more reliably detected with SSQ surveys. At the same time, the lens modulation transfer function (MTF) must fully support the HMD display panel resolution to avoid blurring images seen by users. We used two identical off-the-shelf plano-convex lenses (Edmond Optics 33-384) for each eye, positioned with the convex surfaces of the two lenses facing each other (Figure 2). This design results in a 1.3 meter virtual image distance and creates a sharp image across an 85° field of view. The overall image distortion in our design is more pronounced than the benchmark system described by Geng et al. [Geng et al. 2018]. Additionally, when compared side-by-side with commercially available headsets, our design exhibits a magnitude of pupil swim that is considerably larger.

3.2 Head and Eye Tracking

We also retrofitted our customized Rift with an integrated binocular XR eye tracking platform from Tobii (Tobii AB, Sweden). The eye tracker has a sampling frequency of 240 Hz and is based on Tobii's latest-generation off-axis (direct to eye) solution for VR and AR optical designs. Using this eye tracker, we recorded cyclopean gaze origin and direction and gaze depth. Six degree-of-freedom head position is obtained from the standard OpenXR API and recorded at 240 Hz. We used a custom Matlab toolbox to analyze eye and head movement data (details in supplementary materials).

3.3 Distortion Correction

In our headset we can use ETDDC to reduce the magnitude of pupil swim relative to distortion correction with a static correction mesh. The deliberate introduction of excessive pupil swim via static correction and the corresponding ability to mitigate its presence with ETDDC allows us to reliably introduce additional visual-vestibular conflict in the ETDDC off condition of our user study without relying on manipulations to virtual camera motion. When experiencing our ETDDC implementation, users viewer eye position reported from our eye tracker in combination with Light Field Portals (LFPs) which were previously described by Guan et al. [2022]. The LFP for our lens is generated from optical ray tracing software to perform dynamic distortion correction. Instead of implementing ETDDC within a custom application, we modify an OpenXR implementation to enable distortion correction at the systems level, enabling ETDDC across all Meta PC VR content. We next use this custom ETDDC solution to run a naturalistic VIMS study with a real VR game.

4 User Study Design

Our aim in this user study is to design a protocol to evaluate how much intrinsic headset properties such as pupil swim affect user-reported VIMS symptoms during naturalistic HMD use. Importantly, we want to evaluate VIMS under the "best possible" conditions with content designed to avoid visual discomfort. To achieve these goals, we evaluate VIMS in a multi-session, within-subjects protocol where users play the popular VR game Job Simulator (Owlchemy Labs, Boston, MA) which avoids virtual user motion inconsistent with the user's actual movement. Across the two sessions we use ETDDC to manipulate the amount of pupil swim. In theory, participants will experience less VVC in the ETDDC-enabled session.

4.1 Experimental Design

All participants participated in two 80-minute sessions on different days. Sessions differed based on whether ETDDC was enabled or disabled but were otherwise identical. Session order (i.e., whether ETDDC on or off was conducted first) was counterbalanced across participants. There was a minimum of 24 hours between sessions and on average 9.87 (±1.1) days between sessions. We only included participants who completed both sessions. Of these participants, two dropped out after 60 minutes in one of their sessions, and their data are not included in the analysis. Prior to donning and immediately after doffing our customized Rift HMD, participants completed the SSQ [Kennedy et al. 1993], Misery Scale [Bos et al. 2005], and five questions adapted from the Computer Vision Syndrome Questionnaire [del Mar Seguí et al. 2015] evaluating the experienced severity of annoyance with eye strain, image clarity, and headache related to HMD fit, HMD weight and visual experience.

In Job Simulator player perform various tasks in simulated roles as a chef, office worker, convenience store clerk, and mechanic. Participants completed tasks in each of the jobs for 20 minutes in standardized order (Figure 3). Participants verbally completed the Misery Scale and CVS-Q surveys at the midpoint and end of each 20 minute block while remaining in headset. We logged gaze position and head rotation/translation data throughout each session, and participants performed an eye tracking calibration at the beginning of each job.

4.2 Participants

Thirty-eight participants (16 male, 22 female) with 20/20 vision without glasses and normal stereoacuity voluntarily took part in the IRB-approved experiment. The mean age of participants was

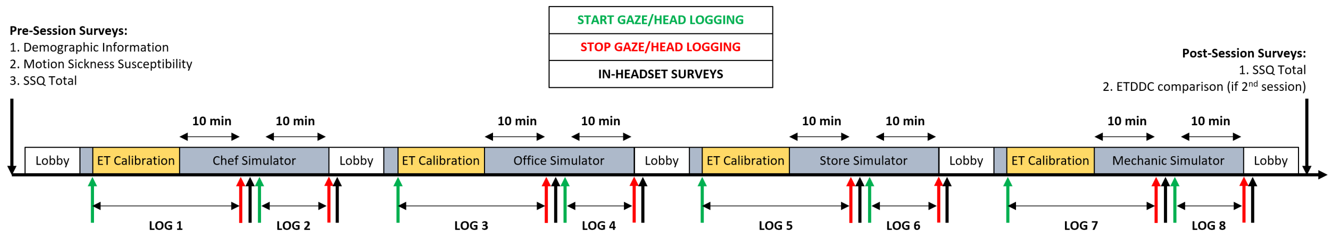

Fig. 3. Study design and timeline of events in each 80 minute user study session. All participants completed two sessions that were identical except for whether ETDDC was enabled or disabled. Time spent in the level selection lobby and eye tracking calibration (ET calibration) was generally between one to three minutes. Our in-headset surveys were completed verbally and we opted for a shorter set of questions using the Misery Scale and Computer Vision Syndrome Questionnaire (CVS-Q) compared to the full Simulator Sickness Questionnaire. Participant gaze behavior, head position, and orientation was logged at 240 Hz. In each session we collected eight logs corresponding to the gaze and head behavior which correspond to the eight sets of CVS-Q and Misery in-headset surveys.

36.6 ±1.4 years. The mean interpupillary distance was 61.2 ±0.4 mm. Mean years of experience using AR/VR technology was 1.9 ±0.3 and mean number of hours spent playing VR per week was 0.7 ±0.2.

4.3 Participant Motion Sickness Susceptibility

VIMS susceptibility has been shown to moderate whether and how a user experiences VIMS while using VR headsets [Golding et al. 2021; Keshavarz et al. 2023; Zhao et al. 2023]. Participants completed the Visually Induced Motion Sickness Susceptibility Questionnaire (VIMSSQ) to assess VIMS susceptibility [Keshavarz et al. 2023], which yields a continuous numerical estimate of susceptibility based on self-reported history of VIMS symptoms. The distribution of VIMMSSQ scores in our sample was not meaningfully different from those expected in the general population: sample VIMSSQ Total mean and median were 26.9 and 20.7 compared to the expected population mean and median of 25.6 and 22.0 [Keshavarz et al. 2023].

5 Effect of Pupil Swim on Visual Comfort

We first evaluate whether pupil swim mitigation through ETDDC affects visual comfort during naturalistic VR use over 80 minutes.

5.1 Impacts on Visual Discomfort and User Preference

To determine whether ETDDC mitigates VIMS symptom severity, we analyzed how participants' SSQ scores varied as a function of time and condition. Figure 1B depicts the average SSQ Total score prior to session start (baseline) and after session completion for both ETDDC enabled (green) and disabled (purple) sessions. Using a mixed-effects linear model, we observed a significant decrease in SSQ Total when ETDDC was on compared to when it was off ($\beta = -8.86 \pm 3.51, t_{111} = -2.53, p = 0.01$), indicating that ETDDC mitigated VIMS symptom severity across the 80-minute play session (full model results are reported in supplementary materials).

Additionally, after playing both sessions, we showed all participants an A/B comparison of the Job Simulator level selection area (similar to an office lobby) with ETDDC enabled and disabled to determine whether the pupil swim present in our system was readily perceptible. More participants reported an image quality preference when ETDDC was enabled (29/38, 76.3%) compared to static distortion correction (9/38, 23.7%) indicating that a majority of participants could see the increased pupil swim without ETDDC. Taken together, we found a clear reduction in visual discomfort without ETDDC and visual preference with ETDDC enabled compared to using a static distortion correction, indicating pupil swim contributes to visual discomfort and a reduced user experience.

5.2 Comparison to Prior Work

We next compare the relative magnitude of experienced discomfort in our naturalistic study task with that observed in previous studies over shorter time durations using SSQ Total scores. The overall average SSQ Total across both sessions in this study was 25.5 ± 18.7. Saredakis et al. [2020] calculated the average SSQ Total values across 55 recent studies investigating VIMS that largely employed non-naturalistic experiences (i.e., using virtual camera motion to induce large VVCs). Broken down by session length, the average SSQ Total for those studies was 23.5 ± 3.2 for studies less than 10 minutes, 33.4 ± 2.9 for studies greater than or equal to than 10 minutes, and 27.4 ± 3.1 for studies greater than or equal to 20 minutes (of which no study included sessions longer than 60 minutes). The observed SSQ Total in this study was not meaningfully different from those observed in previous studies, even though participants in this study played VR for significantly longer. This comparison indicates that after controlling for session length, the overall magnitude of experienced VIMS during naturalistic gameplay may be significantly less than that observed in studies employing intentional manipulations to exaggerate VVC.

Like prior studies, we additionally evaluate SSQ subscales and how demographic factors contribute to experienced VIMS symptom severity. We observed VIMS susceptibility, sex (unlike past studies, we find men experienced more VIMS symptoms than women), and their interaction were significant predictors (see supplementary materials for details and SSQ subscale outcomes).

6 Behavioral Correlates to Visual Discomfort

In an initial 30 minute version of our experiment with 43 different participants, we observed overall smaller values of SSQ Total and did not observe comfort differences between sessions with ETDDC enabled or disabled (details in supplementary materials). It is unclear if this finding indicates that there was no difference in visual comfort at 30 minutes or if surveys were not sensitive enough to detect differences in comfort. While we do not have the data to conclusively answer this question, our within-subjects study design does allow us to examine whether user head and gaze behavior changed significantly between the two ETDDC conditions at different points in time in our 80-minute dataset.

6.1 Representational Similarity Analysis

We used RSA to explore survey, eye tracking, and head tracking data for a number of reasons. First, it provides a holistic view of the entire representational space of the survey and eye tracking behaviors across time and ETDDC conditions. This way, we are not only comparing each feature to an end metric (i.e., SSQ Total) but rather gaining an understanding of how the behavioral metrics and surveys naturally cluster. In Figure 1C, we use multidimensional scaling (MDS) to visualize the dissimilarity matrices to see that the SSQ-defined VIMS is more closely tied to a number of behavioral metrics than abbreviated survey questions we asked during the session (Misery Scale and CVS-Q). Secondly, the RSA framework does not heavily rely on linear assumptions, allowing for exploration of complex, potentially nonlinear relationships between features and conditions, which might be missed by linear models. Lastly, RSA offers a more flexible and adaptable framework for comparing models, as it does not require specific assumptions about the form of the relationship between predictors and the outcome, unlike regression analysis. We add to the flexibility of the RSA framework by finding weights through a Bayesian optimization using a non-parametric objective function, further emphasizing the potential to explore non-linear relationships between VIMS and our surveys and behavioral metrics.

In this experiment, our conditions were defined by the number of repeated time points (10-80 minutes in 10 minute increments) and the conditions (higher and lower SSQ Total sessions rather than ETDDC on or off), which allows us to construct a 16x16 representational dissimilarity matrix (RDM). For the surveys, each of the six RDM matrices represents one of the six questions we asked during the session. For the gaze and head behaviors, each of the RDMs represents one of the 41 gaze or head movement metrics we indexed (eye blink duration, saccade velocity, total fixations, etc.; see the supplementary materials for depiction of the RDMs for each variable). When constructing these RDMs, each participant acts as their own "channel" such that the similarity between conditions is compared across a vector of participants for a given feature. Each index in our RDM represents the Euclidean distance between two 38-length (the number of participants) vectors representing each participant's survey responses or head and gaze behavior at various time points across both study sessions.

6.2 Features Associated with Visual Comfort

We employed Bayesian optimization to identify the optimal linear combination of features that best approximates the target RDM for user comfort (higher or lower SSQ Total difference; see Figure 4A). The process was initiated by subsampling 80% of the participants from the data, a procedure bootstrapped 30 times to create model weights that can better generalize across participants and potentially studies. To ensure that one matrix does not contribute more than another merely due to the magnitude of the measure being collected, we min-max normalized each of the matrices, assigning the lowest dissimilarity score 0 and the highest dissimilarity score 1. This normalization was performed for each of the survey and behavioral metrics. We then initialized weights for the Bayesian optimization such that the sum of weights equaled one. The relative weights were determined by finding the optimal combination of weighted features to maximize the Spearman rank correlation to the target SSQ Total RDM matrix (Figure 4A). The weights were determined over 50 optimization cycles, using the results of the previous optimization to continually refine the best linear combination of feature RDMs. The weights from this process are presented in Figure 4B.

When analyzing all data across both sessions, we found that for the survey scores, the session with higher SSQ Total score was best approximated ($\rho = 0.42$, $p < 0.001$) by headaches from the headset fit (80%), weight (17%) and clarity (3%). For the behavioral metrics, SSQ Total was best correlated ($\rho = 0.85$, $p<0.001$) overwhelmingly by eye blink behavior (80%) followed by vestibulo-ocular reflex (8%), fixations (7%), and saccades (4%). When looking at the magnitude of difference across participants, during sessions with higher motion sickness, participants blinked for longer (approximately 15-30 milliseconds longer, average blink duration of 322 ms across all conditions) and made slower vestibulo-ocular reflex head movements (1-3 degrees/second slower, average 95th percentile rotation speed of 44.2 degrees/second across all conditions. See supplementary materials for more details). We next examine how well the weights found through the optimization were generalized to participant data held out from optimization and found that the eye and gaze behavior weights, when applied to participants that were left out, predicted the higher SSQ Total session better ($p<0.001$) than survey responses (behavioral data $\rho = 0.60$, survey $\rho = 0.41$).

6.3 Temporal Representational Similarity Analysis

Next, we examined how well behavioral metrics and surveys could differentiate between the more and less comfortable sessions at different points in time. If discomfort increases over time, then the initial surveys, collected during periods of time when comfort is relatively similar between the two sessions, may have little predictive power on the user's final levels of visual comfort. Furthermore, the overall discomfort across the 80 minutes may suffer from a mixture of weights and scores during the full experiment. To do this analysis, we used a sliding window approach, in which we used 30-minute windows (reducing our RDMs to $8x8$ matrices), performed the Bayesian optimization from Section 6.2, and moved the window in 10 minutes increments until we captured the full 80 minutes. This windowing approach provides an indication of how well each respective factor can differentiate between higher and lower SSQ Total differences at various points in time. The 30-minute window is a constraint imposed by RSA which requires a meaningful vector length to compute distances between conditions, or in our case, to compute meaningful Spearman rank correlation scores in our target RDM. We can vary the gaze/head behavior window to arbitrary lengths because the data is collected at >90 Hz, however,

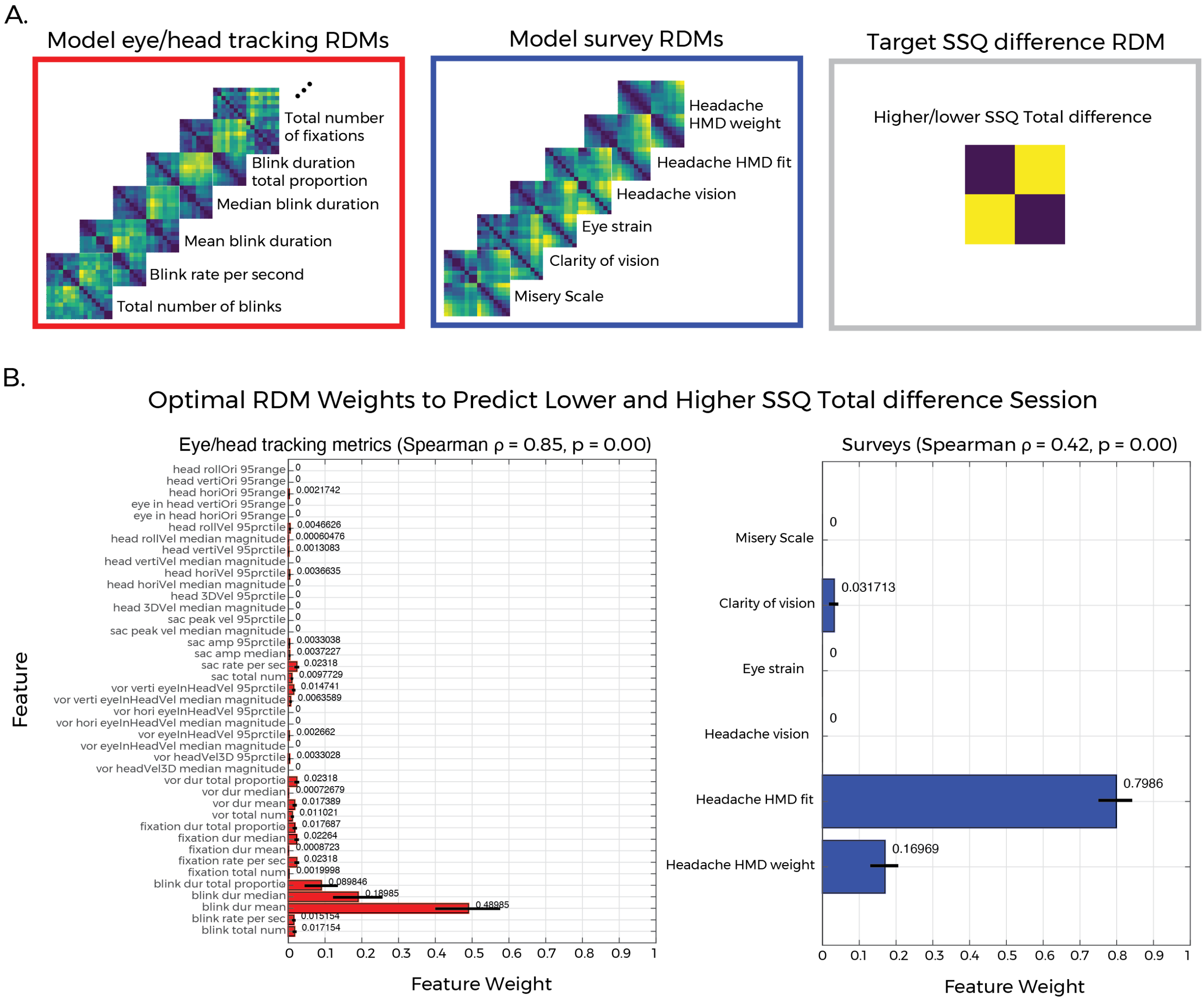

Fig. 4. A. To identify reliable correlates to visual discomfort as reported by the Simulator Sickness Questionnaire, we analyze participant gaze and head movement behavior alongside surveys. We generate a target Representational Dissimilarity Matrix (RDM) where lower and higher SSQ Total sessions are separated into two separate 80-minute blocks comprised of 10-minute intervals (gray Target SSQ RDM, right). Individual questions for in-headset self-report surveys (center) and individual head and gaze summary statistics collected during the study (left) are separated into the same block structure, and these feature RDMs are optimally weighted using the Bayesian optimization procedure outlined in Section 6.2 to best match the target SSQ Total RDM using Pearson rank correlation. B. These resulting features represent the RDMs that most reliably differentiate between the more and less comfortable sessions across our 38 participants. Bars represent mean feature weights and error bars represent standard error of the mean.

in-HMD surveys were only collected in 10-minute intervals so we are constrained to multiples of 10 minutes to maintain consistent comparison between survey and behavioral data.

We found that the survey Spearman correlation gradually increased with time, with later time windows being stronger indicators of simulator sickness (Spearman ρ: 10-40 mins: 0.62, 20-50 mins: 0.79, 30-60 mins: 0.83, 40-70 mins: 0.86, 50-80 mins: 0.86). In contrast, gaze and head tracking metrics were able to indicate simulator sickness earlier, with ρ reaching 0.86 from the first time window, and never falling below it (Figure 5). Thus, it took the survey scores approximately 20 additional minutes to reach the same Spearman correlation from the optimization as the behavioral data. While this Bayesian optimization approach can differentiate between higher and lower SSQ Total user study sessions sooner than surveys in post-hoc analysis, further investigation is required before we can identify broadly generalizeable markers of visual discomfort.

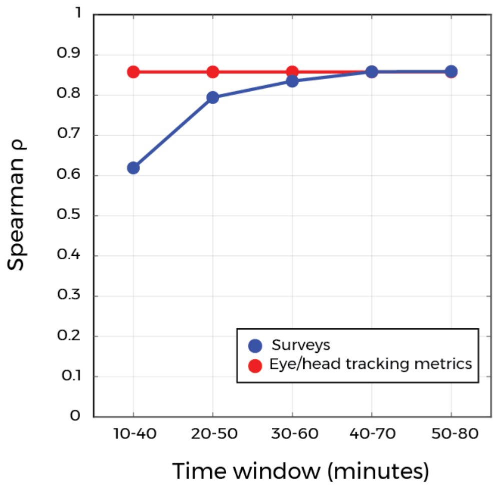

Fig. 5. We repeat the Bayesian weighting procedure from Section 6.2 but restrict the data to 30-minute subset of the total data to examine how well survey and behavioral data can differentiate between higher and lower SSQ Total study sessions over time. Survey responses and behavioral data should diverge across the two study sessions as comfort differences become more pronounced. Participant in-headset survey responses become more reliable predictors of visual comfort over time (Spearman ρ increases from 0.62 to 0.86 over 30 minutes). In contrast, head and gaze statistics are reliable predictors of discomfort within the first time window, and remain predictive throughout the entire experiment (Spearman ρ = 0.86 for all time windows).

7 Discussion

We built a high pupil swim HMD and enabled ETDDC across the entire library of VR content available on the Meta PC VR platform. Leveraging this HMD, we studied the effects of pupil swim on visual comfort over 80 minutes while participants played Job Simulator. We found that ETDDC can mitigate the effects of pupil swim to improve visual comfort and using RSA identified changes in blink and VOR behaviors that are potentially correlated with higher SSQ Total scores. While both abbreviated discomfort surveys (Misery Scale and CVS-Q) and user behavior could predict relative discomfort between our two sessions, behavioral metrics could predict the differences earlier (ρ>0.8 after 40 minutes and 60 minutes for behavior and surveys respectively) and more accurately (ρ = 0.86 and 0.66 after 40 minutes using behavior and surveys respectively). We conclude with some additional thoughts.

Other Sources of VIMS. Multiple sources of visual-vestibular conflict can contribute to VIMS in HMDs, and ETDDC cannot address all of these issues. The repeated-measures study design in this study isolates reduced pupil swim magnitude as the most likely factor that can explain improved visual comfort with ETDDC enabled and underscores the importance of using within-subjects designs to mitigate confounding effects from interpersonal differences in VIMS research.

Generalizability of Behavioral Correlates. Eye and head movement behavior is a function of the observer's task and individual characteristics [Burlingham et al. 2024; Malpica et al. 2023]. Our head and gaze dataset partially addresses this concern because our study is a within-subjects experiment which has participants playing the same game in two different sessions. This enables us to look at relative changes in an individual's behavior, rather than behavioral changes in absolute terms aggregated across all participants. Importantly, our use of ETDDC and pupil swim to induce VIMS, rather than virtual camera motion inconsistent with real user movement facilitates more naturalistic participant behavior. The behavioral changes identified here are more likely to generalize compared to those identified with experiences explicitly designed to induce discomfort. However, the changes in eye and head movement patterns observed in this study when users report elevated visual discomfort still may not generalize to other VR experiences or when factors other than pupil swim induce visual discomfort. Further investigation should be conducted to evaluate whether and how the approaches outlined in this work generalize to other experiences.

Alternatives to RSA. While RSA provides a powerful tool for exploring complex relationships in physiological data, it's important to consider alternative approaches. RSA requires a large number of conditions and can require deeper univariate investigation to find the direction of effects. Regression-based methods, such as Ridge Regression, Lasso, Bayesian regression and Gradient Boosting Regression (GBR), offer alternatives. These techniques can directly model relationships within the feature space, handle multicollinearity, and provide clear measures of feature importance. GBR, in particular, although computationally intensive can capture complex nonlinear relationships effectively. Despite these alternatives, RSA's ability to provide a holistic view of the representational space, capture potentially nonlinear relationships, and when coupled with Bayesian optimization provide interpretable weights make it a valuable tool in data analysis. In addition, RSA provides a framework that can fine tune [McClure and Kriegeskorte 2016] neural network models, providing a bridge to connecting new data to existing VIMS models [Chang et al. 2021; Hell and Argyriou 2018; Islam et al. 2021; Luong et al. 2022; Wen et al. 2024; Zhao et al. 2023].

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