Reduction of Motion Complexity as an Objective Indicator of Cybersickness in Virtual Reality

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Abstract

Subjective measures, such as the Simulator Sickness Questionnaire (SSQ), Fast Motion Sickness Questionnaire (FMS), and discomfort scores, are widely used to assess cybersickness, but they often interrupt the user experience and are prone to bias. To overcome these limitations, researchers have also investigated objective indicators, though some approaches, such as using physiological data, can be cumbersome and impractical. Based on the loss of complexity hypothesis, which suggests that certain conditions, such as disease or aging, can produce a reduction of complexity in physiological system dynamics, we conducted an initial investigation of the relationship between movement complexity and cybersickness. We analyzed motion tracking collected from two previous cybersickness studies using the *d95* score, a complexity metric derived using principal component analysis. The results revealed a systematic relationship between movement complexity and cybersickness across both experiments. Higher discomfort scores were associated with a reduction in complexity, thereby supporting the loss of complexity hypothesis. Furthermore, the 9-DOF complexity measure, which includes both physical head movement and virtual camera motion, was a more sensitive indicator than the 6-DOF measure computed from physical movements alone. These initial findings suggest that movement complexity may be a useful objective indicator for future cybersickness research.

Index Terms: Cybersickness, virtual reality, motion complexity.

1 Introduction

Cybersickness is the most notable and well-studied phenomenon among the various aspects of user comfort, an important subjective metric in virtual reality (VR) [33]. Symptomatology and susceptibility can vary greatly between individuals, which also raises significant accessibility concerns. Unfortunately, despite decades of research, theoretical understanding of cybersickness remains incomplete, and various theories have been proposed to explain its causes [62]. Thus, cybersickness remains an active research topic in the VR community, and empirical studies often make use of both subjective measures and objective indicators that are known to be correlated with user discomfort.

The most common method for measuring cybersickness is through subjective reports. Widely used questionnaires include the Simulator Sickness Questionnaire (SSQ) [25] and Virtual Reality Sickness Questionnaire [30]. Subjective ratings can also be collected more efficiently through a single rating on a numerical scale–most notably the Fast Motion Sickness Scale [26] and discomfort scores [16]–that are often used in field-of-view restriction experiments. While questionnaires are often considered the "gold standard" for evaluating subjective experiences, they can often be unreliable and subject to individual reporting bias [61]. Additionally, in the case of cybersickness, they may even prime the user by suggesting that the experience may induce sickness [78]. Finally, cybersickness often develops gradually over time, and subjective measures are challenging to deploy for continuous monitoring, because they usually require interrupting the VR experience to make an explicit report [7].

To supplement subjective reports, researchers have investigated a variety of methods for evaluating cybersickness using objective measures (e.g. [23, 32, 34]). Physiological signals, such as heart rate and electroencephalogram (EEG), have been shown to be useful indicators of discomfort [10, 24, 34, 66]. However, collecting physiological data requires additional equipment and may also physically encumber the user. Many physiological sensing instruments are also sensitive to noise and become unreliable during movement, which limits their usefulness in virtual reality experiences that involve walking around or physically interacting with the environment. Previous researchers have also proposed that postural data can be an objective predictor of motion sickness, offering a simple way to measure cybersickness using only the VR tracking system [58, 63]. For instance, studies have shown that spontaneous postural sway can indicate individuals who are more susceptible to cybersickness [4, 54, 59, 63].

This work is motivated by the need to explore new ways of utilizing motion tracking data, which is crucial to advancing this line of research into objective indicators of cybersickness. Lipstiz and Goldberger proposed the **loss of complexity hypothesis**, which is based on a systematic review of past research findings and suggests that disease states or aging can degrade the complexity of physiological dynamics [37, 36]. Applying this hypothesis in the context of cybersickness, we analyzed the motion complexity of tracking data from two previously conducted VR cybersickness studies. These motion tracking datasets were provided by the original researchers and had not been previously analyzed in prior reports. Experiment 1 was a mixed-design study involving 38 participants who visited the lab for three sessions, each separated by at least 24 hours, yielding a total of 108 sessions and 541 trials. Experiment 2 was a between-subjects study with 90 participants, resulting in a total of 90 sessions and 458 trials. According to a recent meta-analysis, the number of participants in both experiments are among the largest samples sizes from contemporary VR locomotion experiments [81].

To evaluate motion complexity, we used the *d95* complexity score proposed by Kilteni et al. [28], which is based on principal components analysis (PCA). This measure has recently been shown to be useful in studies that investigated the relationship between motion complexity and embodiment [56, 55, 77]. To the best of our knowledge, this paper represents the first application

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of the *d95* complexity score in the context of cybersickness. This work explored the relationship between motion complexity and cybersickness over the course of exposure. Our analyses focused on individual discomfort scores recorded at the end of each trial rather than the typically reported aggregate discomfort score. As a result, this metric provides a more dynamic view of how cybersickness evolves over the course of exposure for each participant. The results of these analyses revealed a systematic relationship between movement complexity and discomfort score ratings from participants across both experiments. Reduced movement complexity was observed as discomfort increased, which supports the loss of complexity hypothesis and suggests that this approach may be a promising objective indicator for future cybersickness research.

2 Related Works

2.1 The Cause of Cybersickness

Despite none of the existing theories being able to fully explain the causes of cybersickness [62, 67], there are three distinct theories widely cited by researchers.

2.1.1 The Sensory Conflict Theory

The sensory conflict theory attributes cybersickness to a conflict between the visual and vestibular systems. Traditionally, researchers have proposed that modeling the activity of the central nervous system, driven by different sensory inputs, is key to understanding the cause of motion sickness [51, 57]. The theory is based on the assumption that our perceptual systems, such as the vestibular and visual systems, work independently. Our central nervous system therefore has certain expectations for the input of those perceptual systems. When these expectations are violated, as when experiencing virtual locomotion in VR, sickness may occur [57].

Many of those in the VR research community regard this theory as the leading explanation for cybersickness [79, 3, 2, 47]. However, critics argue that it fails to predict motion sickness susceptibility due to the difficulty in knowing an individual's history of environmental interactions [63, 27].

2.1.2 The Postural Instability Theory

The postural instability theory posits that cybersickness results from prolonged exposure to unstable postural control in novel environments [58]. By taking an ecological perspective, this theory considers the perceptual system as a whole. In VR, optically specified motion is often unrelated to the control of the body, as the body is not physically moving [18]. This theory gained popularity among cybersickness researchers seeking objective predictors of cybersickness [21, 72, 10].

2.1.3 Other Theories

The poison theory suggests that the brain interprets the mismatch between visual and vestibular inputs as a sign that poison has been ingested, thus triggering sickness [68]. Despite being widely cited, this theory lacks empirical support and is generally considered invalid [62]. The Differences in Virtual and Physical (DVP) hypothesis proposes that differences between virtual and physical head movements are key to understanding cybersickness [53].

2.2 Measuring Cybersickness

Traditionally, researchers have assessed the severity of cybersickness a user experiences through subjective questionnaires. Meanwhile, objective measures of cybersickness are still under exploration.

2.2.1 Subjective Measures

The Simulator Sickness Questionnaire is the most widely used measure for cybersickness [25]. While it only accounts for a limited range of symptoms [19], it captures some of the key symptoms that users experience. Furthermore, the SSQ does not provide information about users' discomfort levels between the start and end of a VR session. Repeating the SSQ during exposure breaks immersion and may lead to higher reported symptoms due to its demanding characteristics [78, 7].

Researchers have also proposed simpler questionnaires that involve only a single rating, such as the Fast Motion Sickness score [26] and discomfort scores [16]. The FMS asks participants to rate their level of motion sickness on a scale from 0 (no sickness at all) to 20 (frank sickness) [26], while the discomfort score asks participants to rate their discomfort level from 0 (how they felt at the start) to 10 (severe discomfort) [16]. Both FMS and discomfort scores can be administered repeatedly throughout exposure, allowing researchers to capture the time course of motion sickness. Using individual discomfort scores, researchers can calculate the average discomfort score (ADS) and relative discomfort score (RDS) as derived measures. RDS accounts for participants' relative performance if they terminate the session early [16] and has been widely used [9, 48, 75].

McHugh et al. explored the use of a physical dial to measure cybersickness and found it to be significantly positive correlation with other questionnaire results [40]. While subjective measures are widely used to assess cybersickness, they have several limitations that impact their reliability. These include their dependence on the user's ability to judge and recall their discomfort as well as their inability to capture real-time fluctuations in discomfort and sickness levels.

2.2.2 Objective Measures

Motion Data. Feigl et al. studied the feasibility of using gait parameters as cybersickness indicators [15]. While there were multiple correlations found between gait parameters and cybersickness, there was no clear overarching explanation for these correlations. Monteiro et al. found a correlation between the compression rate of users' motion trajectory data and cybersickness levels, utilizing a complexity-based approach [43]. J. Zhao et al. used decomposed 3D motion features to estimate cybersickness, yielding better results compared to methods based on optical flow [80]. G. Zhao et al. explored the correlation between sickness per minute and motion data [79]. To address privacy concerns associated with motion tracking data, Moore et al. discovered that user tracking data could be obfuscated by encoding positional data as velocity data, mitigating privacy risks while still enabling useful analysis [44].

Eye Tracking Data. Lopes et al. studied the correlation of eye behaviors–specifically pupil position and blink rate–and cybersickness [38]. However the results were inconclusive. Despite this, many other researchers have been using eye tracking data in their predictive models [32, 21, 64], which is described in Section 2.2.3.

Physiological Data. Dennison et al. explored using physiological signals to predict cybersickness and identified electrocardiogram (ECG), electrogastrogram (EGG), electroencephalogram (EEG), and heart rate as the most relevant signals [12]. Tian et al. further investigated the connection between EGG, ECG, EEG, and individuals' susceptibility to cybersickness [66]. EEG is the most widely used objective measure for cybersickness. Jeong et al. used EEG data to classify cybersickness with deep learning algorithms [24]. Mimnaugh et al. found that the P3b Event-Related Potential component from EEG could reflect cybersickness symptoms and their impact on users' attention and task performance [42]. Cortes et al. studied the effect of cybersickness on EEG and postural instability, discovering that participants experiencing cybersickness could maintain postural stability at the cost of increased cognitive load, as indicated by reduced alpha power in their EEG data [10]. Li et al. explored EEG brain patterns in individuals resistant to cybersickness, offering new insights into resistance mechanisms [34].

2.2.3 Predictive Models

Evaluating the Stimulus. Early work on cybersickness prediction focused on assessing the discomfort-inducing properties of stimuli. Kim et al. measured exceptional motion in 360° videos to evaluate the level of cybersickness these videos could induce [29]. Padmanaban et al. found that vection and sickness were correlated as a function of relative motion depth, and they developed a model to predict the nauseogenicity of 3D videos [52]. Balasubramanian and Soundararajan created a dataset of 100 videos and predicted discomfort based on camera motion [5]. Du et al. extracted video features such as optical flow and saliency, using a 3D CNN to estimate sickness scores, which were calculated based on the SSQ and MSSQ short forms [13]. However, this approach did not consider the individual differences in cybersickness susceptibility [67].

Modeling the Relationship. Venkatakrishnan et al. used structural equation modeling to explain the relationship between cybersickness, motion control, and presence [69]. Wang et al. used fuzzy logic to integrate various individual factors and found a significant correlation between the composite value and cybersickness severity [73]. Tian et al. proposed the Least Increase Aversion protocol to explore factors contributing to cybersickness [65].

Predicting the Discomfort. Researchers have been working to predict cybersickness severity. Machine learning methods can be applied here, utilizing tools like VRhook to collect labeled datasets [74]. Some studies have used machine learning models such as CNN-LSTM or random forests to predict cybersickness severity based on physiological signals like heart rate and galvanic skin conduction [23, 39]. Islam et al. applied deep fusion techniques to integrate sensor data, achieving 88.77% classification accuracy across four classes using eye-tracking and head-tracking data [21]. They further extended their work by fusing physiological, head-, and eye-tracking data to forecast cybersickness severity over different time horizons [22]. Additionally, researchers have developed interpretable cybersickness detection models using explainable AI [32, 31]. Li et al. proposed an EDA-enhanced kinematic model that utilizes only HMD tracking data [35].

2.3 Motion Complexity and Cybersickness

Kilteni et al. used motion complexity to evaluate the effect of body ownership illusions [28]. They measured motion complexity using $d95$, which is based on principal component analysis (PCA). Peck and Good found that motion complexity is significantly correlated with embodiment [55]. They used the $p95$ scores to measure motion complexity, which represents the number of principal components required to explain 95% of the variance in the data [14]. According to the postural instability theory, motion trajectories may be useful to predict and measure motion sickness [58]. Most previous studies on postural instability have measured the standard deviation of the center of balance or head position.

Lipsitz and Goldberger proposed the *loss of complexity hypothesis* as a framework to explain how disease and aging—both of which impair physiological function—lead to a reduction in the complexity of human physiological outputs. This loss of complexity reflects a diminished ability to adapt to physiological stress [36]. Empirical evidence supporting this hypothesis has been found across various fields, including kinesiology [8], cardiovascular physiology [11], and neurophysiology [17, 45]. In this work, we apply the loss of complexity hypothesis in the context of cybersickness. If a systematic reduction in the complexity of motion can be observed when users experience discomfort during the use of virtual reality systems, then this would provide further empirical support for the loss of complexity hypothesis and also introduce new opportunities for using motion complexity as an objective indicator of cybersickness.

Figure 1: Screenshots of the close-quarter (left) and open virtual environments (right) used in Experiment 1, which share the same layout and only differed in wall height. The task required participants to collect the coins shown in both screenshots by traveling over them.

3 Motion Complexity Calculation

As mentioned in Section 2.3, the loss of complexity hypothesis predicts that a reduction in motion complexity may indicate impaired physiological functions. To test this hypothesis, we used the $d95$ score, a metric that has been employed by VR researchers in other scientific contexts, to measure participants' motion complexity.

3.1 Data Recording

The VR applications in both experiments recorded the local position (x,y,z) and rotation $(yaw, pitch, roll)$ of the head-mounted display ($Head$) relative to its parent during the VR session, capturing the physical motion generated by users with six degrees of freedom (DOF). Experiment 1 recorded data at a frequency of 90 Hz and Experiment 2 recorded data at a frequency of 72 Hz. Additionally, the global position and rotation of the XR camera rig (Rig) were recorded, reflecting virtual motion resulting from users' controller inputs. Virtual locomotion was accomplished using view-directed steering, which meant that only the x- and z-axis translation, along with yaw rotation, of the Rig were changing. Therefore, by including tracking data from the Rig, the motion dataset increases from 6-DOF to 9-DOF $(x_{head}, y_{head}, z_{head}, yaw_{head}, pitch_{head}, roll_{head}, x_{rig}, z_{rig}, yaw_{rig})$.

3.2 Complexity Estimation

Our primary measure, *motion complexity*, was derived from the *d95* head tracker scores as defined in [28]. To estimate this, we first performed PCA on the 6-DOF motion data for each trial using the `prcomp()` method in R. Results from PCA summarize the variance in each dimensionality based on eigenvalues which represents the amount of variance that can be explained by a given principal component. We looped through the array of each data matrix's cumulative proportion of variance (sorted in descending order) to determine the least number of dimensionality needed to account for at least 95% of the variance. For the 6-DOF dataset, we denoted this number as *d95.6d*. Since virtual locomotion is also associated with cybersickness, we appended the motion tracking data from the *Rig* to the 6-DOF dataset, resulting in a 9-DOF dataset. We then calculated a second motion complexity score, *d95.9d*, using the same approach as for *d95.6d*.

4 User Studies

In this paper, we report the key methodological details from the two prior experiments that are pertinent to the motion complexity analysis; the full explanation of the experimental procedures can be

Figure 2: A screenshot of the virtual environment used in Experiment 2. The task required participants to collect the coins and arrows shown in both screenshots by traveling over them.

found in [76] (Experiment 1) and [49] (Experiment 2). Both experiments were conducted in the same laboratory, with study protocols reviewed and approved by the University of Minnesota's Institutional Review Board (IRB). Additionally, the experiments were conducted two years apart and involved different participant pools.

4.1 Experiment 1

4.1.1 Experiment Design

Experiment 1 was originally conducted to investigate the effectiveness of adaptive restriction, a cybersickness mitigation technique that extended the widely used field-of-view (FOV) restrictor by changing the size and shape based on the optical flow in the user's visual field.

The study followed a 2×3 mixed design with the virtual scene as the between-subjects variable (close-quarter environment and open environment) and FOV restriction as the within-subjects variable (symmetric restriction, adaptive restriction, and no restriction). Participants came to the lab for three sessions, each of which was separated by at least 24 hours. Each session lasted approximately 30 minutes total, with about 20 minutes immersed in VR. Participants used an HTC Vive Pro Eye headset and Valve Index controllers to experience the virtual environment.

4.1.2 Procedure

At the first session, participants read the information sheet, gave informed consent, learned how to use the Valve Index controller and immersed themselves in the virtual environment using an HTC Vive Pro Eye headset. During each VR experience, participants stood in place and were free to physically rotate their heads but were instructed not to walk. Virtual translation and rotation were controlled using the controller's thumbstick, with a translation velocity set at 2.5 meters per second and a rotation velocity of 45° per second. Participants finished a short practice trial before beginning 10 consecutive experimental trials, each lasting approximately 2 minutes, for an overall immersion time of about 20 minutes. In each trial, participants navigated along a predefined path marked by coins. As depicted in Figure 1, the close-quarter virtual environment featured 3-meter-high walls, while the open environment had 0.15-meter-high walls. After completing each trial, participants rated their discomfort on a scale of 0 to 10 using a virtual slider within the VR interface. Participants also completed the Simulator Sickness Questionnaire (SSQ) both before and after the VR experience.

4.1.3 Participants

A total of 38 participants (19 male, 19 female) completed all three sessions of the study. They were recruited from the university community and ranged in age from 19 to 27 (*M*=22, *SD*=2.46).Self-reported video game experience varied from little to over 10 years of gaming experience. To be eligible, participants had to be at least 18 years old, able to stand without assistance, have normal or corrected vision, not be pregnant, and have no history of severe motion sickness. Participants were compensated with a $20 gift card. Due to technical errors in the recorded data from two participants, this analysis includes data from 36 participants (18 male, 18 female).

4.2 Experiment 2

4.2.1 Experiment Design

Experiment 2 was originally conducted to evaluate a novel cybersickness reduction technique called "peripheral teleportation" (PT). The study followed a between-subjects design with three conditions: PT, black FOV restriction, and no restriction (control). Participants visited the lab for a single session that lasted approximately 45 minutes, with about 25 minutes immersed in VR. The experiment used a Meta Quest 2 headset with Oculus Link.

4.2.2 Procedure

When participants came to the lab for their session, they first read the information sheet, gave informed consent, learned how to use the Meta Touch 2 controller, and immersed themselves in the virtual environment using a Meta Quest 2 headset. The required body posture, motion constraints, and locomotion interface was the same as Experiment 1 (see Section 4.1.2). The translation velocity was 3 meters per second while the rotation velocity was 45°. Participants finished a short practice trial before they completed 10 consecutive experimental trials. Each experimental trial took about 2.5 minutes to finish, resulting in an overall immersion time of approximately 25 minutes For each trial, they navigate a predefined path marked by coins and arrows. The virtual environment was a city about $130m \times 100$ m in size. At the end of each trial, they rated their discomfort score on a scale of 0 to 10 using a virtual slider in VR.

4.2.3 Participants

A total of 90 participants (45 male, 45 female) participated in Experiment 2. Participants' ages ranged from 19 to 27 years old (*M* = 23.57, *SD* = 2.67). Self-reported video game experience was also varied, ranging from little to over 10 years of gaming experience. Participants were recruited from the university community through classroom announcements, email lists and posted flyers. In order to be eligible, they had to be over the age of 18, able to stand without assistance, have normal or corrected vision, not be pregnant, and have no history of severe motion sickness. Participants were compensated with either extra credit or a $15 Amazon gift card. Data from all 90 participants was included in this analysis.

4.3 Measures

SSQ Scores. For both experiments, the Kennedy-Lane Simulator Sickness Questionnaire (SSQ) [25] was used to assess the severity of a participant's sickness symptoms. The SSQ was administered twice within each session, once prior to VR exposure in order to gain a baseline, and then again after the exposure. We took the difference between the pre- and post- exposure responses to calculate the total severity of symptoms.

Discomfort Scores. At the end of each trial, participants reported their subjective discomfort based on a scale from 0 to 10 using a slider inside VR. If participants reported a 10, the experiment would immediately terminate in addition to participants having the option to manually terminate the experiment. In the original analyses for these experiments, average discomfort scores (ADS) and relative discomfort scores were computed for each condition using the procedure from Fernandes and Feiner [16]. However, for this new investigation of motion complexity, we did not aggregate per-trial data into ADS and RDS, because we are interested in a finer-grained analysis of the data across all trials.

Task Duration. The VR application recorded task duration by the overall time spent on the navigation task, which is defined as the time between when they started and stopped moving in each trial.

Visibility and Presence. Participants completed a post-experiment questionnaire assessing visibility and presence using a 7-point Likert scale to rate their agreement with the following statements:

- **Visibility**: It was difficult to see the virtual environment during locomotion.
- **Presence**: I had a sense of being present in the virtual environment.

Motion Tracking Data. Motion tracking data was recorded as described in Section 3. In some cases where participants terminated the experiment in the middle of a trial, the data from that trial was excluded from the analysis. A total of 15 trials were excluded from Experiment 1, and 9 trials were excluded from Experiment 2.

4.4 Hypotheses

Using data from each experiment, we investigated the following hypotheses regarding the effects of motion complexity and cybersickness:

- **H1.A**: In Experiment 1, participants would report lower discomfort scores in the optical flow restrictor condition compared to the control condition.
- **H1.B**: In Experiment 2, participants would report lower discomfort scores in the peripheral teleportation condition compared to the control condition.
- **H2**: In both experiments, higher *d95.6d* scores will be associated with lower discomfort ratings from participants.
- **H3**: In both experiments, higher *d95.9d* scores will be associated with lower discomfort ratings from participants.

Hypotheses **H1.A** and **H1.B** were included to confirm previously reported effects on cybersickness reduction using the individual discomfort scores instead of the aggregated discomfort scores that were previously reported in prior works. Individual discomfort scores were used in order to better monitor cybersickness effects throughout the course of exposure because discomfort scores were queried at multiple points in the experiments. This allows for a finer-grained analysis of the data across all trials. **H2** and **H3** are completely new hypotheses to evaluate the motion complexity measure proposed in this paper.

5 Results

5.1 Discomfort Scores Distribution

We conducted a distribution analysis on the collected discomfort scores from both Experiments 1 and 2, similar to prior research [23]. For both Experiments 1 and 2, the quantile distributions of discomfort scores are the same and are listed as follows. The first quantile of the distribution was 1, the second quantile of the distribution was 4, and the third quantile of the distribution was 7.

5.2 Statistical Model

We used a linear mixed-effects model (LMM) to investigate the influence of *d95.6d*, *d95.9d*, and Mitigation conditions on participants' individual discomfort score ratings. The distribution of participants' discomfort score ratings was not normal because it was an ordinal rating from 0 to 10. However, because it has a relatively large number of levels and equal intervals, it is reasonable to treat discomfort scores as continuous. Additionally, LMMs are robust to assumption violations [60] and have been previously used for evaluation when assumptions are violated [1], in particular for discomfort scores [70].

We programmed the LMM with the *lmer*4 package in R [6], following the procedure recommended by Müller et al. [46]. First, we used a forward stepwise linear regression to identify possible predictors of the discomfort score ratings out of the following candidate variables: *Mitigation, d95.6d, d95.9d, presence, visibility,* and *virtual environment*. At each step, we chose variables based on p-values and stopped when the AIC was equal to Mallow's C_p to control the total number of variables in the final model. Starting with the six factors that we have already know to predict cybersickness [69], the forward stepwise linear regression model reduced them to three, which were *Mitigation, d95.6d,* and *d95.9d*. For the rest of the factors, we did not observe a significant impact. This general regression equation is shown in Equation 1.

$$\text{discomfort score} \sim \text{mitigation} + \text{d95.6d} + \text{d95.9d} + (1 \mid \text{id}) \quad (1)$$

5.3 Experiment 1

Mitigation Technique. The analysis revealed a significant effect of mitigation technique ($B = -1.73, SE = .60, t = -2.86, p = .005$), which indicate that participants' discomfort scores were 1.73 points lower with the adaptive restrictor. These results confirm the previously reported main effect using the linear mixed-effects model, thus supporting the validity of analyzing discomfort scores on a per-trial basis.

Motion Complexity. We found that both *d95.6d* ($B = -0.66, SE = .24, t = -2.66, p = .008$) and *d95.9d* ($B = -0.47, SE = .12, t = -3.62, p < 001$) had a significant impact on the discomfort scores, suggesting that the requirement of one additional axis to explain the tracking data variation is associated with a decrease of approximately .66 (*d95.6d*) and .47 (*d95.9d*) in discomfort scores, respectively. These results are shown in Figure 3.

5.4 Experiment 2

Mitigation Technique. The analysis revealed a significant effect of mitigation technique ($B = -2.15, SE = .54, t = -3.99, p < .001$), which indicated that participants' discomfort scores are 2.15 points lower with PT. These results confirm the previously reported main effect using the linear mixed-effects model, thus supporting the validity of analyzing discomfort scores on a per-trial basis.

Motion Complexity. We found that only *d95.9d* ($B = -0.66, SE = .29, t = -2.25, p = .02$), but not *d95.6d* ($B = -0.56, SE = .32, t = -1.73, p = .08$), had a significant impact on the discomfort score ratings, which suggested that one additional axis required to explain the tracking data variation (*d95.9d*) is associated with a decrease of approximately .66 in discomfort scores. These results are shown in Figure 4.

6 Discussion

6.1 Motion Complexity and Cybersickness

The results revealed a systematic relationship between motion complexity, measured using *d95.6d* and *d95.9d*, and user discomfort across two virtual reality cybersickness experiments. These findings support the loss of complexity hypothesis, which posits that disease states or aging can produce a reduction of complexity in the dynamics of many physiological systems. It is worth noting that these results do not contradict previous evidence in support of postural instability theory. Complexity and postural sway are derived from different motion characteristics, and less complex motion does not necessarily mean stabilized posture. Similarly, a reduction in motion complexity could also be consistent with sensory conflict theory, as a physiologically effect produced by motion sickness, rather than an underlying cause.

From a practical perspective, motion complexity represents a potentially useful objective indicator for cybersickness research. Due to its ability to be computed directly from motion tracking data without any additional instrumentation, it can be readily applied in

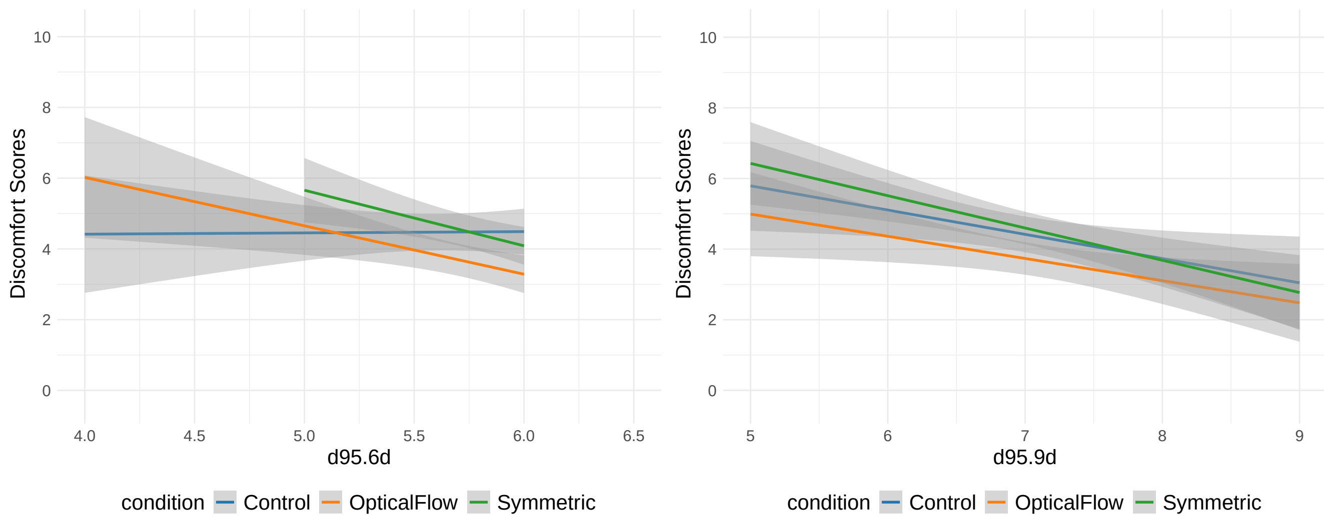

Figure 3: **(Left)** A line graph illustrating the impact of *d95.6d* (x-axis) on participants' discomfort score ratings (y-axis) across trials in Experiment 1. Each solid line represents a linear regression line for each of the three FOV restriction conditions: no restriction, optical flow adaptive restriction, and symmetric restriction. The shaded grey areas around the lines represent the confidence intervals for each smooth. The graph demonstrates that lower *d95.6d* scores are associated with higher reported discomfort levels, particularly in the optical flow adaptive and symmetric restriction conditions. **(Right)** A line graph illustrating the impact of *d95.9d* (x-axis) on participants' discomfort score ratings (y-axis) across trials in Experiment 1. The figure shows that lower *d95.9d* scores are correlated with higher reported discomfort levels.

a wide variety of experimental procedures, including data collected from previous studies.

The extension of the 6-DOF motion complexity measure used in previous work with three additional degrees of freedom from virtual locomotion is another contribution of this paper. Since cybersickness is strongly associated with continuous virtual movement that does not align with physical motion, we expected that the 9-DOF motion complexity measure would provide a more sensitive indicator. This intuition was consistent with our results; the effect for *d95.6d* was only significant in Experiment 1, while *d95.9d* was significant for both experiments. Future work could also consider incorporating additional dimensions, such as controller motion tracking data. This would be valuable to evaluate whether a reduction in movement complexity is measurable in other body parts, and could also potentially improve its sensitivity as an objective indicator of cybersickness.

6.2 Limitations and Future Work

This paper presents initial evidence in support of motion complexity as an objective indicator of cybersickness. However, further investigation is necessary to validate its use as a measurement instrument. Meehan et al. [41] defined valuable measurement instruments as *reliable* (able to produce repeatable measures both within and across subjects), *valid* (measures the underlying construct), *sensitive* (ability to discriminate amongst multiple outcome levels), and *objective* (well protected against bias from the subject and the experimenter). Motion data is inherently objective, and although our analyses of data from two prior experiments is promising, validation of the other three criteria is beyond the scope of this initial inquiry. Future evaluations will need to build upon this work to replicate and generalize these results across a wider variety of virtual reality systems, scenarios, and users.

The results reported in this paper were derived from motion tracking data collected using two consumer-grade VR systems. Previous studies have shown that the such systems are not immune to error; for example, an evaluation of the SteamVR 1.0 tracking system observed an offset in tilt between the real and virtual ground plane when tracking is lost and reacquired [50]. The Oculus Quest 2, which was used in Experiment 2, has been reported to have superior accuracy and precision compared to the SteamVR 2.0 tracking system used in Experiment 1 [20]. It should be noted that in both experiments, participants were instructed to stand in place without turning their body, and virtual movement and turns were primarily accomplished using the handheld controller. This reduces the likelihood of motion tracking errors that may occur when walking around a physical room. Therefore, evaluation of movement complexity during physical locomotion tasks using wide-area VR tracking systems would be valuable in future work.

Seeing as the motion complexity measure relies upon principal component analysis (PCA), future studies will need sufficiently large sample sizes to achieve sufficient sampling adequacy. It is generally agreed upon that approximately $n = 100$ is needed for a single group model while $n \geq 150$ is needed to compare between groups. For example, Peck and Good analyzed experiments with $n = 189$ and $n = 99$ while Experiment 2 had $n = 90$ [55]. However, it is possible to use a smaller number of participants as long as there are approximately 100 sessions worth of data [71]. In this paper, Experiment 1 only had $n = 36$, but the within-subjects design required each participant to complete three separate VR sessions, resulting in a total of 108 sessions across the entire experiment. As previously noted, both experiments considered in this paper had larger sample sizes than the majority of contemporary VR locomotion studies [81], and future research may not be able to replicate these findings in smaller-scale studies.

It should also be noted that the *d95* score is not the only potential way to quantitatively represent motion complexity. Other models, such as multiscale entropy [11], have also been proposed in the literature. We believe that investigating different approaches for modeling movement complexity and comparing their utility would be a worthwhile endeavor for future cybersickness research.

7 Conclusion

This paper explored the relationship between motion complexity and cybersickness by analyzing motion tracking data from two previous cybersickness studies using the *d95* complexity score. Our results support the loss of complexity hypothesis, showing that re-

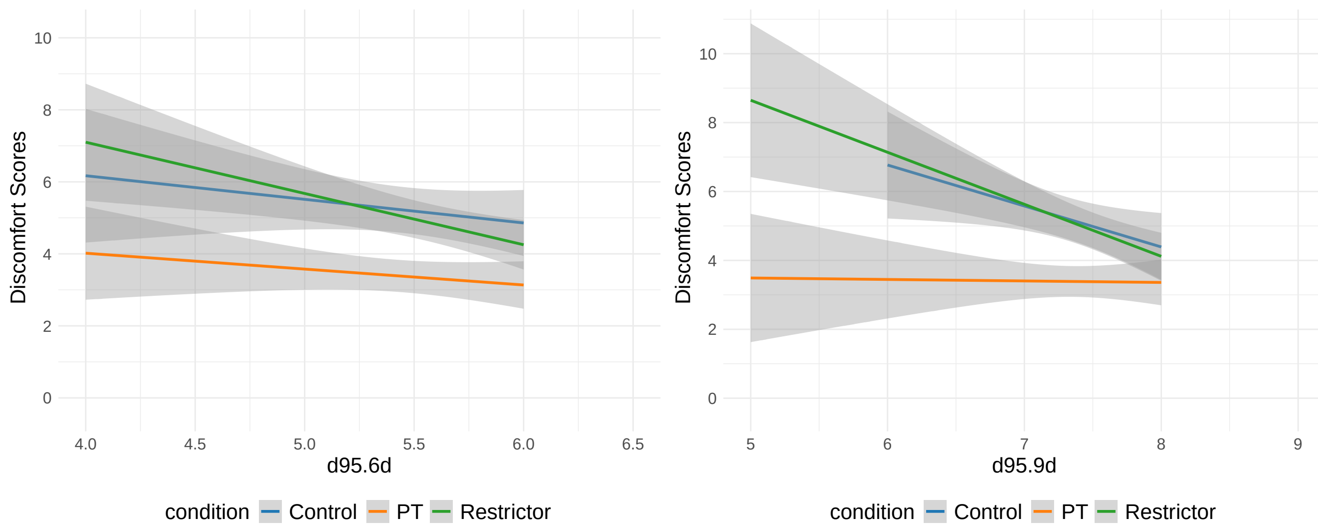

Figure 4: **(Left)** A line graph illustrating the impact of *d95.6d* (x-axis) on participants' discomfort score ratings (y-axis) across trials in Experiment 2. Each solid line represents a linear regression line for each of the three mitigation conditions: no restriction, FOV Restriction, and Peripheral Teleportation (PT). The shaded grey areas around the lines represent the confidence intervals for each smooth. **(Right)** A line graph illustrating the impact of *d95.9d* (x-axis) on participants' discomfort score ratings (y-axis) across trials in Experiment 2. The figure shows that lower *d95.9d* scores are correlated with higher reported discomfort levels. The graph demonstrates that lower *d95.9d* scores are significantly associated with higher reported discomfort levels, particularly in FOV restrictor and PT conditions.

duced motion complexity is associated with increased discomfort during the VR experience. Notably, the 9-DOF complexity measure, which includes both physical head movement and virtual camera motion, was a more sensitive indicator than the 6-DOF measure computed from physical movements alone. Motion complexity offers a promising, objective indicator of cybersickness that can be computed from VR head tracking data without requiring additional equipment. While these initial findings are encouraging, further research is needed to validate motion complexity as a reliable and sensitive measure across different VR systems, virtual environments, and user groups. By refining this approach, motion complexity could become a valuable tool for predicting and potentially mitigating cybersickness.

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