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Toward Adaptive VR Design: Physiological and Cognitive Predictors of Cybersickness in Serious Games

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ABSTRACT

Cybersickness limits the usefulness of virtual reality (VR) for serious games. Multivariate cybersickness prediction has been studied widely, but mostly on tightly controlled stimuli rather than free-play settings. We examined a small set of theory-motivated predictors in a VR fishery-management simulation with 105 participants, recording heart rate variability (HRV), galvanic skin response (GSR), and heart rate (HR), and collecting post-session ratings of cognitive load and session duration. Hierarchical regression on 94 complete cases explained 35.8% of cybersickness variance ($R^2 = 0.358$, $F(7,86) = 6.84$, $p < 0.001$). Duration dominated ($\beta = 0.87$), followed by cognitive load ($\beta = 0.52$) and GSR ($\beta = 0.54$); HR was marginal ($\beta = 0.45$, $p = 0.052$); HRV correlated bivariately ($r = -0.24$) but was attenuated in the multivariate model. Duration, cognitive load, and GSR are candidate inputs for adaptive comfort systems in serious-game VR.

KEYWORDS

Virtual reality; cybersickness; adaptive interfaces; human-centered design; physiological computing

1. Introduction

Cybersickness produces adverse symptoms during VR use, including nausea, disorientation, and eye strain, with studies estimating that 40–80% of users experience some degree of discomfort (Rebenitsch & Owen, 2016; Saredakis et al., 2020). The problem is particularly acute for serious games used in education and training, where cybersickness drives participant dropout, reduces learning outcomes, and creates negative associations with training content (Hell & Argyriou, 2018; Radianti et al., 2020; Servotte et al., 2020). Because VR systems generate sensory output that must be reconciled with users' embodied expectations, sustained discomfort terminates interaction and undermines the educational value of immersive content. Understanding which user-state variables track cybersickness severity is therefore a prerequisite for adaptive VR systems that adjust interaction parameters based on real-time user monitoring (Caserman et al., 2021; Chang et al., 2020).

A growing body of work has examined multivariate and multimodal cybersickness prediction, combining physiological signals with head- and eye-tracking and behavioral features (Islam et al., 2022; Long et al., 2025; Martin et al., 2020; Tasnim et al., 2024). These studies show that integrative models can clearly outperform single-predictor analyses; explained variance reaches roughly $R^2 \approx 0.75$ in controlled experimental contexts (Martin et al., 2020). Two limitations of this literature motivate the present work. First, most of these predictive models are evaluated on tightly controlled VR exposures, such as roller-coaster simulations or fixed-trajectory videos, rather than on free-play serious-game environments where users self-pace their engagement, encounter motion stimuli of varying intensity, and drive their own narrative progression. Second, the goal in much of this work is predictive accuracy rather than interpretable effect-size estimation tied to specific theoretical mechanisms. Adaptive VR design depends partly on knowing whether cybersickness can be predicted, but also on knowing which

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user-state variables carry the most actionable signal under realistic deployment, and on how those signals map onto candidate intervention points.

We address these gaps by examining a small, theory-motivated set of predictors of cybersickness severity in an ecologically valid serious-game setting. Data come from 105 participants who played a free-play VR fishery-management simulation that mixes stationary first-person interaction with scripted passive-vehicle motion sequences. Using hierarchical multiple regression, we evaluate the relative contribution of physiological measures (HRV, GSR, HR), session-level exposure (duration), and self-reported cognitive load to a global cybersickness severity rating. Our intent is not to compete on predictive accuracy with existing benchmarks; it is to give designers an interpretable, comparative ranking of predictors that can inform adaptive interfaces in serious-game VR.

The contributions of the paper are as follows. We provide a multivariate evaluation of physiological and cognitive cybersickness predictors in a free-play VR serious-game context, complementing the existing predictive models trained on controlled stimuli. We explicitly map each predictor to the theoretical mechanism it is intended to capture (autonomic arousal, vagal regulation, cumulative exposure, attentional resource competition), so that the rationale for predictor selection is transparent. We then derive design implications for adaptive VR serious games from the comparative ranking and effect magnitudes, framed as hypotheses for follow-up experimental and real-time-adaptation work rather than as evidence-based prescriptions.

2. Background and related work

2.1. Cybersickness as an HCI challenge

Cybersickness manifests through three symptom clusters: nausea, oculomotor disturbance (eye strain, headache, focusing difficulty), and disorientation (vertigo, postural instability) (Kennedy et al., 1993). The Simulator Sickness Questionnaire (SSQ) developed by Kennedy and colleagues remains the standard subjective measure (Bimberg et al., 2020; Kennedy et al., 1993).

From an HCI perspective, cybersickness represents a failure of the user experience to remain comfortable under sustained use. Chang et al. (2020) reviewed the phenomenon in this journal as a multifactorial outcome shaped by content design, display technology, and individual user factors, and emphasized that progress on causes and measurement is a prerequisite for improving human-VR interaction quality.

2.2. Theoretical frameworks

Four complementary frameworks guide our predictor selection. Figure 1 summarizes the conceptual model: physiological and cognitive–experiential user-state predictors feed into a regression that, in turn, can inform real-time adaptation of VR interaction parameters.

2.2.1. Sensory conflict theory

Reason and Brand (1975) proposed the dominant explanation: motion sickness arises when sensory inputs conflict with each other or with prior expectations (Oman, 1990). In VR, visual motion signals self-movement while the vestibular system detects no physical motion, producing a fundamental sensorimotor conflict that is hypothesized to drive the autonomic and cognitive symptoms of cybersickness.

2.2.2. Postural instability theory

Riccio and Stoffregen (1991) proposed that motion sickness occurs when postural stability is compromised. This ecological account links susceptibility to individual differences in postural control, with measurable changes in postural stability and autonomic arousal preceding the onset of subjective symptoms.

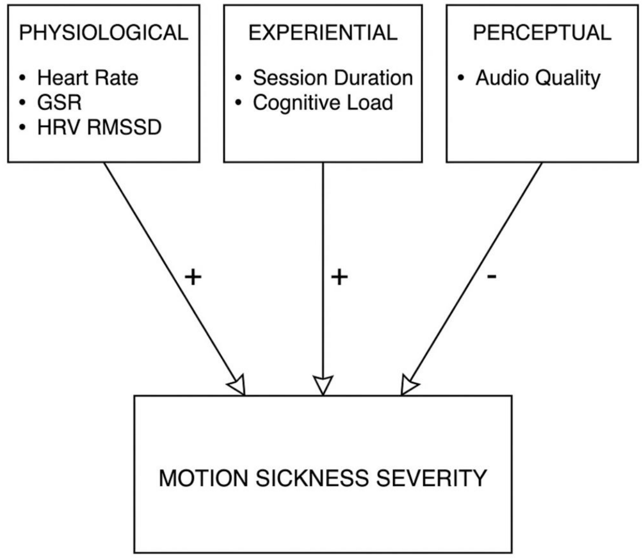

Figure 1. Conceptual framework for adaptive VR design. User-state predictors include physiological measures (HRV, GSR, heart rate) and cognitive-experiential factors (duration, cognitive load). These predictors inform real-time adaptation of VR interaction parameters.

2.2.3. Presence–cybersickness relationship

Weech et al. (2019) reviewed evidence that presence and cybersickness are negatively related, with the connection driven by the efficiency of sensory integration. Higher presence indicates more effective integration of conflicting sensory cues, and interventions enhancing presence tend to reduce cybersickness.

2.2.4. Exhausted brain theory (EBT)

Monteiro and Liang (2025) recently proposed an energy-based account of visually induced motion sickness. In this view, symptoms emerge when the cumulative metabolic and attentional cost of resolving sensorimotor mismatches exceeds the user's available regulatory resources. EBT therefore treats cybersickness as a depletion phenomenon driven by sustained reconciliation effort, and it is particularly relevant to free-play VR, where exposure duration, cognitive load, and autonomic regulation all draw on the same finite resource pool. EBT motivates the joint inclusion of duration, cognitive load, and autonomic markers (HRV) as predictors that should converge on a multivariate signature of energetic depletion.

2.3. Mapping theoretical mechanisms to predictors

We make the rationale for predictor selection explicit in Table 1, which summarizes how each variable in our regression is intended to capture a particular theoretical mechanism. The mapping makes clear why we prioritize these variables over other plausible candidates from the literature, and it gives a basis for interpreting the comparative effect magnitudes reported in the Results.

2.4. Physiological predictors and adaptive systems

Physiological measures provide objective indicators of user state that complement subjective reports and supply real-time data streams for adaptive VR systems. Heart rate variability (HRV), specifically root mean square of successive differences (RMSSD), reflects parasympathetic nervous system activity, and lower HRV—indicating reduced vagal tone—has been associated with increased cybersickness severity (Dennison et al., 2016; Guna et al., 2019; Krokos & Varshney, 2019). Electrodermal activity, measured as galvanic skin response (GSR), reflects sympathetic nervous system activation; GSR tends to increase during cybersickness episodes, with higher values corresponding to greater discomfort

Table 1. Mapping of theoretical mechanisms to operational predictors.

Theoretical mechanism	Operational predictor	Source
Sympathetic activation in response to sensorimotor conflict	GSR, HR	Reason and Brand (1975) ; Kim et al. (2005) ; Dennison et al. (2016)
Parasympathetic / vagal regulation of conflict response	HRV (RMSSD)	Riccio and Stoffregen (1991) ; Dennison et al. (2016) ; Weech et al. (2019)
Cumulative exposure / energetic depletion	Session duration	Saredakis et al. (2020) ; Monteiro and Liang (2025)
Attentional resource competition between sensory integration and task demands	Cognitive load	Hell and Argyriou (2018) ; Monteiro and Liang (2025)

(Kim et al., 2005), and EDA-based predictive models have achieved strong detection accuracy (Dennison et al., 2016; Guna et al., 2019; Hua et al., 2024).

Physiological computing uses real-time physiological data to drive interface adaptations (Fairclough, 2009). In the VR context, this could in principle support dynamic reduction of visual motion intensity, modulation of field-of-view restrictions, or triggering of rest breaks when physiological indicators suggest elevated cybersickness risk; however, the efficacy of any specific adaptive policy remains a matter for prospective evaluation rather than something established by the existing observational literature.

2.5. Cognitive load and user experience

Session duration is one of the most consistent predictors of cybersickness severity, with longer exposure associated with increased symptom accumulation (Islam et al., 2021; Saredakis et al., 2020). Cognitive load during VR tasks is hypothesized to contribute through attentional-resource competition: sensory integration processes share finite cognitive resources with task demands (Hell & Argyriou, 2018; Servotte et al., 2020). This creates a particular tension in serious-game design, where educational depth requires sustained attention and therefore high cognitive load, while excessive cognitive demand has been associated with greater cybersickness. Characterizing cognitive load's contribution alongside autonomic and exposure-time predictors is therefore directly relevant to task segmentation strategies and to adaptive difficulty systems.

2.6. Multivariate and multimodal prediction approaches

A growing body of research has moved beyond single-predictor analyses to evaluate cybersickness through multivariate and multimodal models. Martin et al. (2020) reported a regression-based detection model combining physiological signals with machine learning, achieving $R^2 \approx 0.75$ in a controlled study with a comparable sample size ($N = 103$). Islam et al. (2022) developed a multimodal deep-fusion network that combined physiological, head-tracking, and eye-tracking signals to forecast cybersickness onset. Tasnim et al. (2024) extended this line of work by examining personalization techniques for cybersickness prediction across individuals. More recently, Long et al. (2025) introduced a multimodal physiological modeling approach with high predictive accuracy on standardized VR exposures. Together, these studies show that multivariate physiological and behavioral fusion can clearly outperform single-predictor models for cybersickness detection.

Two characteristics of this literature still leave room for a complementary approach. First, the predictive models above are typically trained and evaluated on tightly controlled VR stimuli, such as roller-coaster simulations, fixed-trajectory videos, or standardized motion clips, rather than on free-play serious-game environments where the user paces their own engagement, faces motion stimuli of varying intensity, and decides when to stop. Second, the optimization target in most of this work is predictive accuracy, rather than interpretable effect-size estimation tied to specific theoretical mechanisms. Adaptive VR design has more uses for the second kind of evidence: it relies on knowing which user-state variables carry the most actionable signal under realistic deployment, not only on whether cybersickness can be predicted at all. The present study contributes to that gap rather than to predictive accuracy benchmarks.

3. Materials and methods

3.1. Study design

We conducted a cross-sectional observational study examining predictors of cybersickness severity in a VR serious-game context. Each participant completed a single VR session, during which we recorded physiological data continuously and collected self-reported cognitive–experiential measures immediately post-session.

3.2. Participants

We recruited 105 participants from the university community. The sample included 54 males (51.4%), 49 females (46.7%), and 2 identifying as other (1.9%). Age ranged from 18 to 52 years ($M = 28.8$, $SD = 8.0$).

Inclusion criteria: age 18–55 years, normal or corrected-to-normal vision and hearing, no history of vestibular disorders. Exclusion criteria: current vestibular medication, severe motion sickness susceptibility based on screening, prior experience with the specific VR application.

All participants provided written informed consent. The Research Ethics Committee of Electronic Engineering Polytechnic Institute of Surabaya approved the study.

3.3. Apparatus

3.3.1. VR hardware

Meta Quest 3 standalone headset (resolution 2064×2208 per eye, 120 Hz refresh rate) with integrated spatial audio.

3.3.2. Physiological sensors

Polar H10 chest strap for heart rate and R-R interval recording. We calculated HRV metrics from R-R intervals. Shimmer3 GSR+ unit for electrodermal activity measurement. Two electrodes attached to the non-dominant hand.

3.4. VR application

We used "Fisherman Manager VR," a serious game developed in Unreal Engine 5.3. The game teaches sustainable fishery management (Damastuti et al., 2025, 2024a, 2024b, 2024c). Players manage a small-scale fishing operation from a beach-side station in first-person VR. Figure 2 shows the main visual elements of the application: the beach-side management desk with its vintage radio and monitor (panel a); the in-game music player interface (panel b); the tablet weather display under stormy conditions (panel c); and the calm-ocean view with the boat management interface (panel d).

3.4.1. Gameplay mechanics

Players make decisions about fishing operations. They monitor weather conditions, fish populations, and economic sustainability through an in-game tablet. The game uses dynamic difficulty adjustment via Q-learning and fuzzy logic (Damastuti et al., 2024c). A dynamic day-night cycle runs each in-game day at approximately 10 real-world minutes (Damastuti et al., 2024a).

3.4.2. Motion-stimulus profile

The application combines a stationary first-person interaction mode with scripted passive-motion sequences. Two categories of visual motion stimulus are theoretically relevant to cybersickness, and the application includes only the second:

(a) user-controlled artificial locomotion. None. The game has no joystick-based translation, no teleportation, no smooth artificial locomotion, and no other user-driven displacement of the virtual

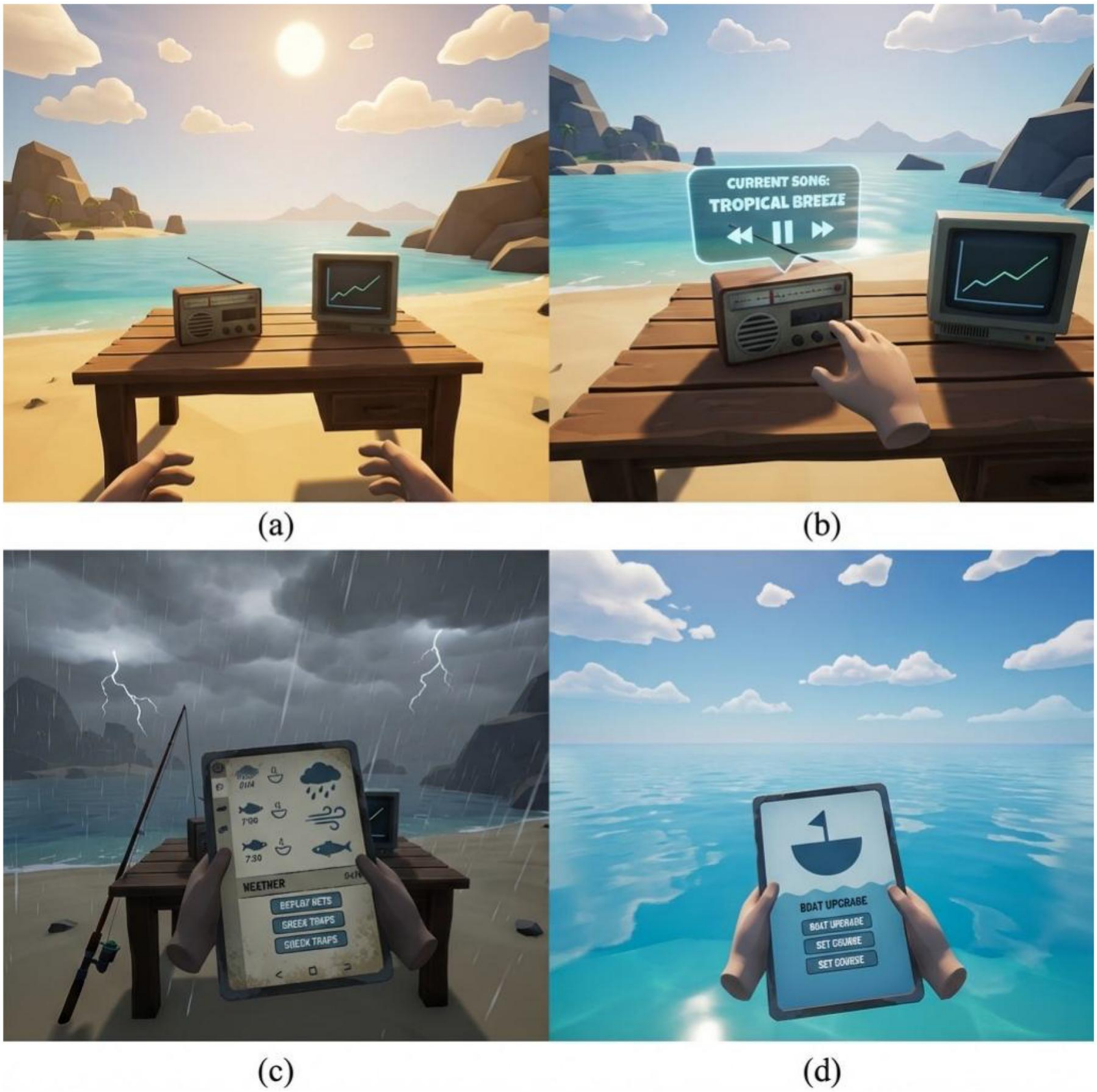

Figure 2. Screenshots from Fisherman Manager VR: (a) Beach-side management station with desk, vintage radio, and monitor; (b) music player UI interaction; (c) stormy weather with tablet showing weather data; (d) calm ocean view with boat management interface.

viewpoint. Players sit at a fixed beach-side management station for most of the session and interact with the environment through gaze-based selection and controller input from that stationary vantage point.

(b) scripted passive vehicle and environmental motion. Present. During boat sequences, players experience passive vehicle motion: the virtual viewpoint translates without user control of direction. Ocean-wave simulation also produces oscillatory peripheral motion throughout the session, and dynamic weather effects (rain, wind, storm transitions) introduce time-varying optic-flow patterns. Passive vehicle motion is a well-known cybersickness trigger because it generates a visually induced self-motion percept (vection) without matching vestibular input (Reason & Brand, 1975), so boat sequences are expected to contribute disproportionately to symptom accumulation within a session.

We make this distinction explicit because "locomotion" is sometimes used narrowly to mean user-controlled translation, and sometimes more broadly to mean any visual self-motion. Our application is stationary in the first sense and includes passive motion in the second. The implication for our analysis is that we cannot separate predictor effects during passive-motion segments from those during stationary segments, which we discuss as a limitation in Section 5.7.

3.5. Measures

3.5.1. Dependent variable

We assessed cybersickness using a single-item 10-point severity rating administered immediately after the session (1 = no sickness, 10 = extreme sickness). The Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993) is the established gold-standard instrument, and it provides subscale scores for nausea, oculomotor disturbance, and disorientation. We chose a single-item global rating for two reasons. First, the sessions varied in length from 10 to 45 min and followed physiologically taxing free-play VR exposure, so minimizing the post-session questionnaire burden was a practical priority for retention and data quality. Bimberg et al. (2020) review SSQ administration in VR and discuss the tradeoffs of briefer measures when subscale resolution is not the analytic target. Second, our analytic goal is to compare effect sizes for a small set of predictors against a single outcome, rather than to predict separate symptom clusters. The cost of this choice is that we cannot recover predictor relationships specific to the nausea, oculomotor, or disorientation subscales, so we list subscale-level prediction with the full SSQ as a direction for follow-up work in Section 5.8. We treat the construct validity of single-item global severity ratings as a separate methodological concern that we acknowledge in the limitations (Section 5.7).

3.5.2. Physiological predictors

Physiological predictors entered into the regression as session-mean values, computed from continuous recordings collected during the VR exposure. A 5-minute pre-exposure baseline was recorded for sensor calibration and signal-quality verification, but it was not used to compute baseline-corrected change scores; only session-mean values were retained in the analytic dataset. Baseline-corrected change scores would partially account for inter-individual variability in resting autonomic activity, and we revisit this preprocessing limitation in Section 5.7.

- **Heart Rate Variability (HRV):** Root mean square of successive differences (RMSSD) in milliseconds, computed from R-R intervals recorded during the VR session.
- **Galvanic Skin Response (GSR):** Mean skin conductance level in microsiemens (μ S) over the session.
- **Heart Rate (HR):** Mean beats per minute over the session.

3.5.3. Cognitive-Experiential predictors

- **Session Duration:** Total time in VR (minutes).
- **Cognitive Load:** Self-reported as Low, Moderate, or High (coded 1–3).

3.5.4. Demographics

We recorded age and gender as control variables.

3.6. Procedure

Participants arrived at the laboratory and completed informed consent and demographic questionnaires. We then attached and calibrated the physiological sensors and recorded a 5-minute pre-exposure baseline for sensor verification. Participants then donned the VR headset and started the gameplay loop. Session termination was engagement-driven: participants were asked to play until they reached a natural stopping point in the management cycle (for example, completing a fishing day or an operational cycle) or until they chose to stop. A 45-minute upper bound was applied as a safety limit on cumulative VR exposure. The observed range of 10 to 45 min ($M = 25.4$, $SD = 8.6$) reflects this voluntary, engagement-driven protocol. Because session length therefore varied with participant engagement and tolerance rather than under experimental control, we are explicit about this when interpreting the session-duration effect in Section 4.3 and in the limitations (Section 5.7).

After exposure, participants removed the headset and completed the cybersickness severity rating and experiential questionnaires. We then removed the sensors and debriefed participants.

3.7. Data analysis

We used hierarchical multiple regression (Cohen, 1988) to examine predictors of cybersickness severity. Continuous predictors were standardized (z-scored) prior to analysis so that the beta coefficients can be compared directly. Cognitive load was coded ordinally (Low = 1, Moderate = 2, High = 3), and gender was dummy-coded (Male = 1, Female/Other = 0). Predictors were entered in four theoretically motivated blocks:

- Block 1: Demographics (Age, Gender)
- Block 2: Session characteristics (Duration)
- Block 3: Physiological measures (HRV, GSR, Heart Rate)
- Block 4: Cognitive factors (Cognitive Load)

For each block we report R^2, the change in R^2 (ΔR^2), and the corresponding F-change test for the increment in explained variance.

We checked multicollinearity using variance inflation factors (VIF), applying the conventional threshold of VIF < 5 as the cutoff for acceptable collinearity (O'Brien, 2007). Effect size was evaluated with Cohen's f^2, where values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects (Cohen, 1988). We also checked the standard regression assumptions: the Shapiro–Wilk test on residuals (normality), the Breusch–Pagan test (homoscedasticity), residuals-versus-fitted plots (linearity), and Cook's distance and leverage values (influential observations). Diagnostic plots are reported in Section 4.4. Analyses were run in Python with the `statsmodels` library at a significance threshold of $\alpha = .05$.

4. Results

4.1. Descriptive statistics

Table 2 presents descriptive statistics for key variables. Cybersickness severity scores ranged from 1 to 10 ($M = 4.15$, $SD = 2.54$), indicating mild-to-moderate average severity with substantial individual variation, consistent with prior VR research (Saredakis et al., 2020).

4.2. Correlation analysis

Table 3 reports the bivariate Pearson correlations between cybersickness severity and each predictor, and Figure 3 visualizes the correlation matrix as a heatmap. Session duration showed the strongest correlation ($r = .456$, $p < .001$), followed by cognitive load ($r = .346$, $p < .001$), GSR ($r = .314$, $p < .01$), HRV ($r = -.238$, $p < .05$), and heart rate ($r = .214$, $p < .05$). The bivariate associations all run in the directions predicted by theory.

4.3. Hierarchical regression analysis

We fit the hierarchical regression on the 94 participants with complete data on all physiological predictors. Table 4 shows the blockwise progression of model fit, including R^2, ΔR^2, F-change, and the significance of each block addition. The full model (Block 4) explained 35.8% of the variance in cybersickness severity ($R^2 = .358$, Adjusted $R^2 = .305$, $F(7, 86) = 6.84$, $p < .001$, Cohen's $f^2 = 0.56$, a medium-to-large effect size).

The blockwise progression makes it clear where the explanatory power in our model comes from. Demographics on their own (Block 1) explained essentially no variance ($\Delta R^2 = .002$, $p = .92$). Adding

Table 2. Descriptive statistics for key variables (N = 105).

Variable	M	SD	Min	Max
Cybersickness (1–10)	4.15	2.54	1	10
Age (years)	28.81	8.03	18	52
Duration (min)	25.43	8.60	10	45
HRV RMSSD (ms)	45.73	15.07	15	85
GSR (μ S)	7.83	4.73	0.8	19.0
Heart Rate (BPM)	78.81	14.46	52	115

Table 3. Bivariate Pearson correlations with cybersickness severity.

Variable	r	p	N	Sig.
Duration	+.456	< .001	105	***
Cognitive Load	+.346	< .001	105	***
GSR	+.314	.001	102	**
HRV RMSSD	−.238	.017	100	*
Heart Rate	+.214	.031	102	*

* $p < .05$, ** $p < .01$, *** $p < .001$.

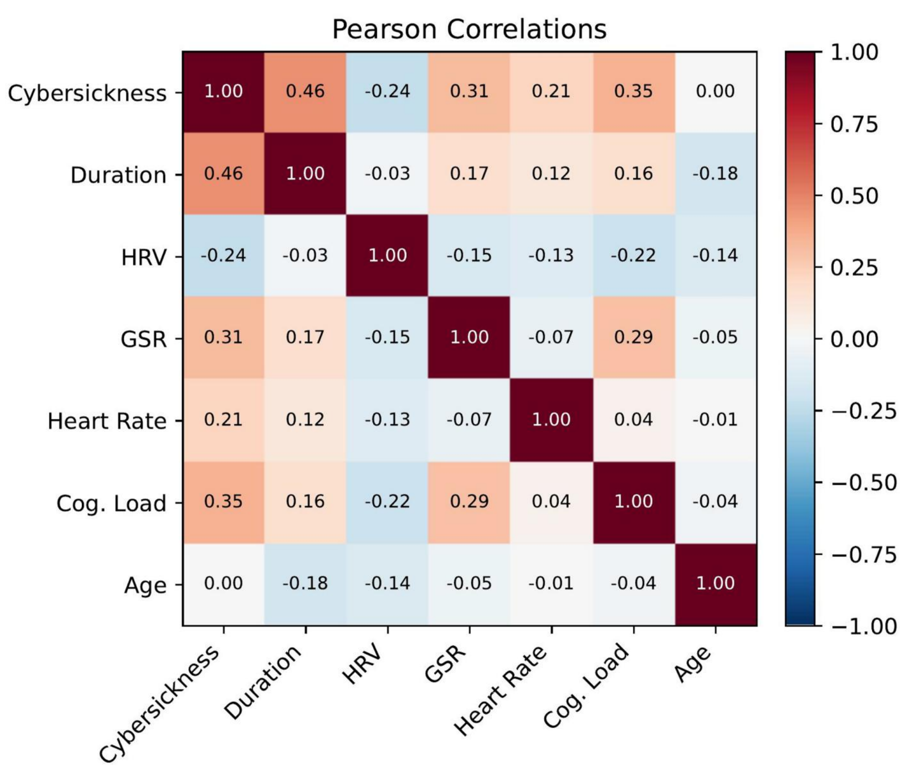

Figure 3. Pearson correlation heatmap of the cybersickness severity outcome and the predictor variables used in the regression.

Table 4. Blockwise hierarchical regression predicting cybersickness severity ($N = 94$).

Block	R^2	Adj. R^2	ΔR^2	F-change	df	p -change
1: Demographics	.002	−.020	.002	0.09	2, 91	.917
2: + Duration	.188	.161	.186	20.63	1, 90	< .001
3: + Physiological (HRV, GSR, HR)	.322	.276	.134	5.75	3, 87	.001
4: + Cognitive Load (Full model)	.358	.305	.035	4.70	1, 86	.033

session duration (Block 2) produced the largest single increment in fit ($\Delta R^2 = .186$, $F(1, 90) = 20.63$, $p < .001$). The physiological measures (Block 3) added another 13.4% of explained variance ($\Delta R^2 = .134$, $F(3, 87) = 5.75$, $p = .001$). Cognitive load (Block 4) added a further 3.5% on top of the physiological block ($\Delta R^2 = .035$, $F(1, 86) = 4.70$, $p = .033$). The increment was statistically significant in every block after the first.

Table 5. Final model: Standardized coefficients with 95% confidence intervals ($N = 94$).

Predictor	β	SE	95% CI	p	Sig.
Duration	+0.871	0.231	[+0.411, + 1.331]	< .001	***
GSR	+0.544	0.237	[+0.072, + 1.015]	.024	*
Cognitive Load	+0.522	0.240	[+0.044, + 1.000]	.033	*
Heart Rate	+0.446	0.226	[−0.003, + 0.896]	.052	†
HRV RMSSD	−0.324	0.232	[−0.786, + 0.138]	.167	
Age	+0.301	0.228	[−0.152, + 0.754]	.189	
Gender (Male)	−0.085	0.448	[−0.975, + 0.804]	.849	
R^2			.358		
Adjusted R^2			.305		
$F(7, 86)$			6.84, $p < .001$		
Cohen's f^2			0.56 (medium–large)		

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

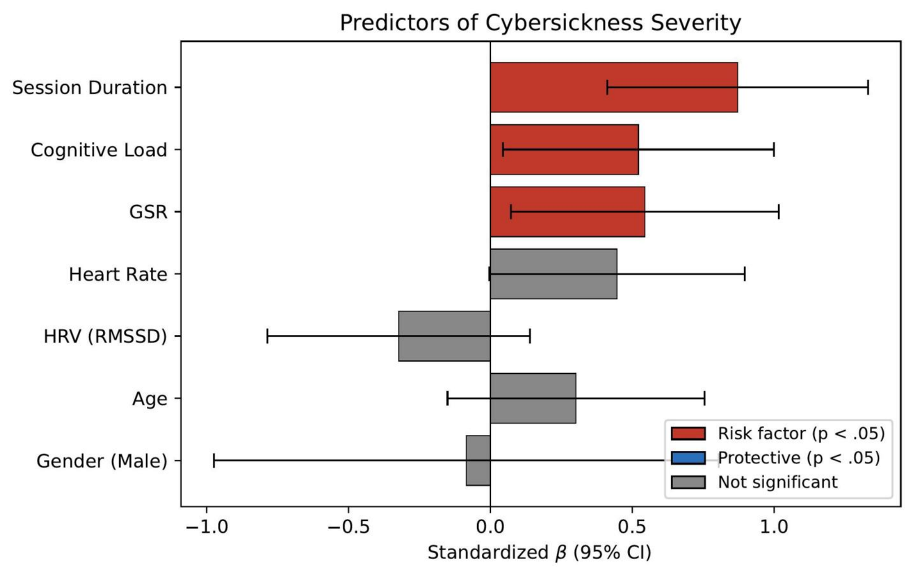

Figure 4. Standardized regression coefficients (β) for all predictors in the full model. Error bars show 95% confidence intervals. Red bars indicate significant risk factors ($p < .05$); blue bars indicate significant protective factors; grey bars are not significant.

Table 5 reports the full-model standardized coefficients with 95% confidence intervals, and Figure 4 visualizes the same coefficients for ease of comparison. Three of the seven predictors reached conventional statistical significance in the full multivariate model.

4.3.1. Session characteristics

Duration was the dominant predictor ($\beta = 0.871$, 95% CI $[+0.411, +1.331]$, $p < .001$). Longer VR exposure was strongly associated with higher cybersickness severity, in line with meta-analytic findings (Saredakis et al., 2020) and with EBT predictions of cumulative depletion (Monteiro & Liang, 2025). Because session duration varied with voluntary engagement rather than under experimental control (see Section 3.6), the directional interpretation here is associative, not causal: longer exposure may produce more cybersickness, but participants who tolerate discomfort better may also keep playing longer. We come back to this endogeneity concern in Section 5.7.

4.3.2. Physiological predictors

GSR was a significant predictor in the multivariate model ($\beta = 0.544$, $p = .024$), with higher tonic skin conductance linked to greater cybersickness. This pattern fits with sympathetic activation in response to sensorimotor conflict (Dennison et al., 2016; Kim et al., 2005). The GSR effect strengthened further in the influence-diagnostic sensitivity refit ($\beta = 0.629$, $p = .007$; Section 4.4), which supports its directional robustness. Heart rate was marginal in the full sample ($\beta = 0.446$, $p = .052$) but became conventionally significant in the sensitivity refit ($\beta = 0.514$, $p = .019$). HRV (RMSSD) showed a significant bivariate correlation ($r = -.238$, $p < .05$), but in the multivariate model it dropped to non-significance

($\beta = -0.324,\ p = .167$). Several factors plausibly contribute to the HRV attenuation: limited statistical power for marginal effects in a complete-case sample of $N = 94$, the use of raw session-mean values without baseline correction (Section 3.5.2), and field-deployment measurement noise. The data do not require a strong shared-variance interpretation, since the observed inter-correlations among the autonomic measures are weak (Section 4.4). Under HC3 heteroscedasticity-robust standard errors (Section 4.4), the GSR and HR effects shift to marginal. We read this as a robustness caveat for those two specific coefficients rather than evidence against the directional pattern, given that the sensitivity refit moved the same coefficients in the opposite direction.

4.3.3. Cognitive factors

Cognitive load was a significant predictor in the full model ($\beta = 0.522,\ p = .033$). Higher self-reported cognitive demand during gameplay was associated with greater cybersickness. This fits attentional-resource accounts where sensory integration competes with task demands for finite cognitive resources (Hell & Argyriou, 2018), and with EBT predictions that cognitive demand contributes to the depletion of the regulatory resources needed to suppress symptoms (Monteiro & Liang, 2025).

4.3.4. Demographics

Neither age ($\beta = 0.301,\ p = .189$) nor gender ($\beta = -0.085,\ p = .849$) was significant in the multivariate model.

4.4. Multicollinearity and regression diagnostics

Variance inflation factors ranged from 1.04 to 1.19 across all predictors, well below the conventional threshold of 5 (O'Brien, 2007), so multicollinearity is not a concern. Residual normality was checked with Shapiro–Wilk and was not violated ($W = .994,\ p = .960$). Residuals-versus-fitted plots showed no obvious linearity violations.

4.4.1. Heteroscedasticity and HC3 robust standard errors

The Breusch–Pagan test was marginally significant ($LM = 18.31,\ p = .011$), suggesting possible mild heteroscedasticity. We therefore re-estimated the model using HC3 heteroscedasticity-robust standard errors. Under HC3, the inferential pattern shifts a little: Duration ($p = .002$) and Cognitive Load ($p = .043$) keep their conventional significance, while GSR ($p = .060$) and Heart Rate ($p = .071$) become marginal rather than nominally significant. HRV stays non-significant ($p = .179$). We therefore read the physiological coefficients as suggestive rather than confidently established, and we frame the design implications in the Discussion in the same way.

4.4.2. Influential observations

Cook's distance flagged seven observations above the conventional threshold of $4/n = .043$ (maximum Cook's $D = .142$). A sensitivity refit that excluded these seven observations ($N = 87$) actually produced a stronger overall fit ($R^2 = .426,\ F(7, 79) = 8.38,\ p < .001$). Duration ($\beta = +0.92,\ p < .001$), GSR ($\beta = +0.63,\ p = .007$), Heart Rate ($\beta = +0.51,\ p = .019$, which is conventionally significant in the refit), and Cognitive Load ($\beta = +0.43,\ p = .047$) all kept or gained significance, while HRV ($\beta = -0.25,\ p = .240$) and the demographic predictors remained non-significant. We keep the full-sample analysis as the primary reported model to avoid post-hoc selection on residuals, and we present the refit as a robustness check that supports the directional pattern of the reported predictors.

Figure 5 shows the diagnostic plots: a Q–Q plot of the residuals, residuals against fitted values, a residual histogram, and the Cook's distance for each observation.

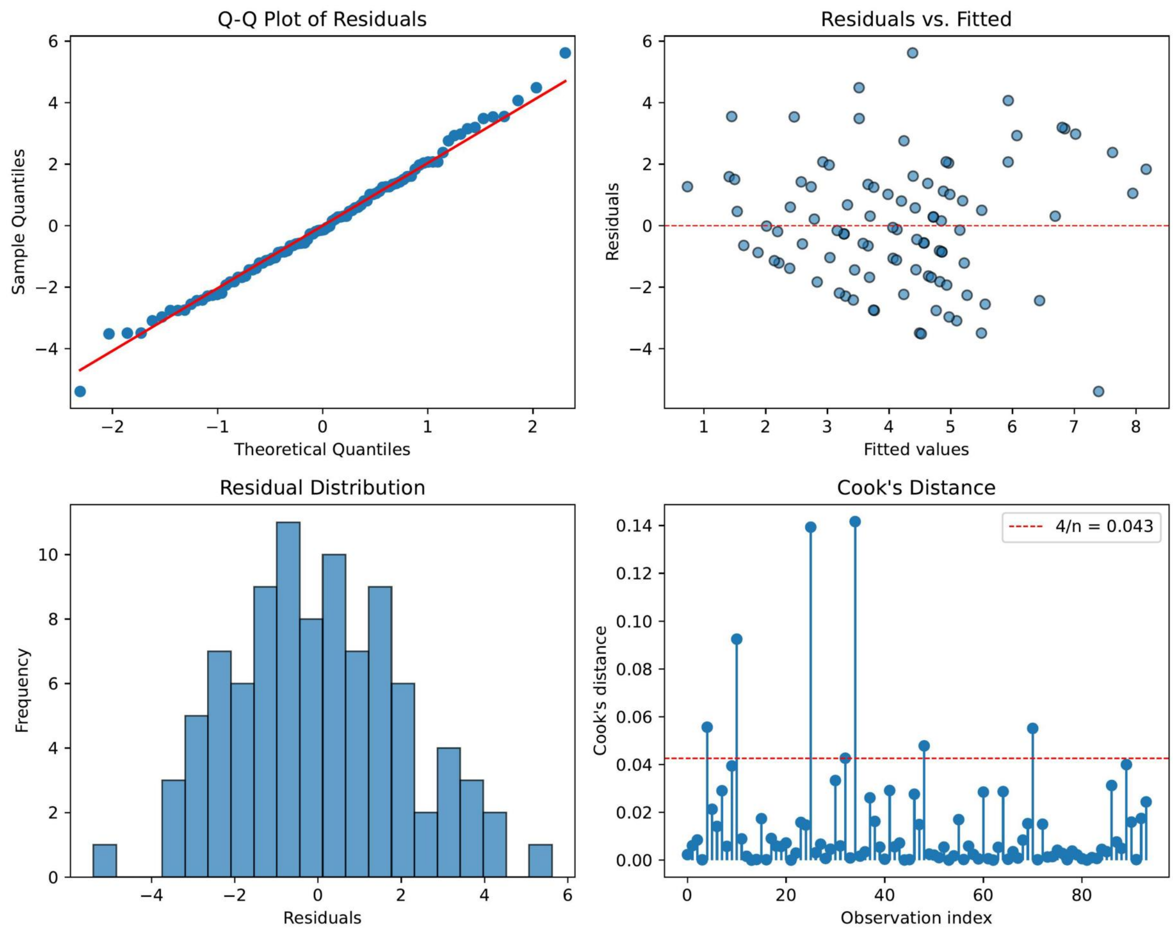

Figure 5. Regression diagnostics for the full hierarchical model. Top-left: Q–Q plot of standardized residuals against the theoretical normal quantiles, used to assess residual normality (Shapiro–Wilk $W = .994$, $p = .960$). top-right: residuals against fitted values, used to check linearity and homoscedasticity. Bottom-left: histogram of residuals. Bottom-right: Cook's distance for each observation, with the conventional $4/n$ threshold drawn for reference; seven observations exceed the threshold and are examined in the sensitivity refit reported in the text.

5. Discussion

5.1. Summary of findings

This study evaluated a small, theory-mapped set of physiological and cognitive–experiential predictors of cybersickness severity in a free-play VR serious-game context. Hierarchical regression on the 94 complete cases explained 35.8% of the variance in self-reported cybersickness severity. Three predictors were significant in the full multivariate model: session duration, GSR, and cognitive load. Heart rate was marginal in the full model and became conventionally significant in the influence-diagnostic sensitivity refit (Section 4.4). HRV correlated with cybersickness in the bivariate analysis but was attenuated in the multivariate model. We read these results as a comparative effect-size estimate for theory-mapped predictors in ecological serious-game VR. They complement existing predictive work on controlled stimuli and motivate specific design hypotheses for adaptive interfaces.

5.2. Comparison to prior predictive work

The 35.8% explained variance reported here is more modest than the 75% reported by Martin et al. (2020) for a regression-based detection model on a similar sample size, and it is lower than the predictive accuracies achieved by recent multimodal deep-fusion architectures (Islam et al., 2022; Long et al., 2025; Tasnim et al., 2024). Two factors plausibly account for this gap. First, those studies optimized predictive accuracy on tightly controlled VR exposures (such as roller-coaster simulations or fixed-trajectory videos) using non-linear machine-learning models that capture complex interactions between physiological signals. The present study used linear hierarchical regression with five theory-mapped predictors in a free-play context, where users self-pace their engagement, face motion stimuli of varying intensity, and decide for themselves when to stop. Second, our outcome was a single-item global severity rating, not a continuous physiologically-derived sickness indicator or a symptom-cluster subscale, which limits how much variance can be explained in principle. We therefore present the reported R^2 not as a state-of-the-art predictive benchmark, but as a defensible estimate of how much parsimonious linear models built on theory-mapped predictors can explain in ecologically valid serious-game VR. The value here is interpretability and effect-size comparison rather than predictive accuracy. The directional ranking of predictors is comparable across our full-sample model and the sensitivity refit ($R^2 = .426$, Section 4.4), so the predictor pattern is robust to outlier sensitivity.

5.3. Implications for adaptive VR design

Our results suggest several candidate directions for adaptive VR systems. We frame them as testable hypotheses for follow-up experimental and prototyping work, not as evidence-based prescriptions, since our cross-sectional observational design does not evaluate the efficacy of any adaptive intervention.

5.3.1. Physiological signals as candidate inputs to adaptive interfaces

GSR was the strongest single physiological predictor across our analyses. The directional effect was consistent in the bivariate analysis ($r = .314$), the full multivariate model ($\beta = .544$, $p = .024$), and the sensitivity refit ($\beta = .629$, $p = .007$). Under HC3 robust standard errors the effect attenuates to marginal significance, so GSR is suggestive rather than definitive in our data; even so, the consistent direction makes it the most informative single autonomic signal we recorded. Combined with cumulative session time, GSR is a plausible candidate input for adaptive comfort systems in serious-game VR (Fairclough, 2009), although the efficacy of any specific adaptive policy will need prospective evaluation. Real-time physiological computing of this kind currently requires research-grade external sensor add-ons; current mainstream consumer headsets (the Meta Quest 3 supports head- and hand-tracking; the Quest Pro additionally supports eye- and face-tracking) do not include direct autonomic sensing.

5.3.2. Session duration as the dominant practical lever

Duration was by far the largest single contributor to model fit. The interpretation has to be cautious because of the engagement-driven termination protocol (Section 3.6), but the size and consistency of the effect across the bivariate and multivariate analyses suggests that exposure-time management is the most accessible single design lever in serious-game VR. Two candidate hypotheses are worth testing in follow-up work: that duration thresholds combined with user-state monitoring outperform fixed time limits, and that personalized exposure ceilings based on early-session physiological response further reduce symptom incidence.

5.3.3. Cognitive load as a serious-game-specific tension

The cognitive load finding is particularly relevant for educational VR, where learning objectives demand sustained engagement but high cognitive demand is associated with greater cybersickness. This is consistent with attentional-resource accounts (Hell & Argyriou, 2018) and with EBT predictions of regulatory depletion (Monteiro & Liang, 2025). We hypothesize that adaptive difficulty systems integrating cybersickness risk signals alongside performance metrics will balance engagement and comfort better than systems that optimize performance alone.

5.4. Theoretical implications

The pattern of effects is broadly consistent with several cybersickness frameworks. The positive bivariate associations with GSR and HR fit sensory conflict theory (Reason & Brand, 1975) and postural instability theory (Riccio & Stoffregen, 1991), both of which predict elevated autonomic arousal in response to sensorimotor mismatch. The negative HRV–cybersickness relationship in the bivariate analysis fits Weech et al. (2019) on sensory integration as a shared substrate of presence and cybersickness, and the broader literature on vagal tone as an index of regulatory capacity.

The pairing of session duration, cognitive load, and reduced HRV as predictors fits the multivariate signature predicted by Exhausted Brain Theory (Monteiro & Liang, 2025): symptoms emerge when the cumulative metabolic and attentional cost of sensorimotor reconciliation exceeds the user's regulatory resources. EBT offers a unifying account for why these particular predictors cluster, since each one indexes a different dimension of resource expenditure (cumulative exposure, current attentional load, baseline regulatory capacity). We read this as supportive of EBT but not diagnostic of it; designs that manipulate energetic demand directly would be needed for a stronger evaluation.

One pattern in our data deserves a direct theoretical comment. The three autonomic measures in our regression, GSR, HR, and HRV, showed weak inter-correlations ($|r| \leq .15$ between any pair), and only GSR retained robust multivariate significance. This is consistent with a view in which different autonomic channels carry partially independent information about cybersickness in free-play VR. GSR (sympathetic activation) carries the strongest single signal, and HRV (parasympathetic regulation) contributes mostly through its bivariate relationship with severity. From a design standpoint, the implication is that the marginal predictive value of multi-channel autonomic monitoring may be smaller than the cost of adding more sensors, especially for deployment-oriented systems where GSR can be acquired with a single inexpensive sensor. We treat this as a hypothesis that needs replication, since the limited power and the absence of baseline correction in the present study (Section 5.7) caution against treating the HRV null as definitive. The practical takeaway for adaptive-system design is that GSR is the physiological signal to instrument first.

5.5. Design implications for VR serious games

Our findings motivate a number of design hypotheses for future evaluation. We frame them deliberately as candidate directions that need controlled testing, not as evidence-based prescriptions.

1. **Adaptive exposure management.** Adaptive break suggestions calibrated to cumulative duration and user-state monitoring are a plausible alternative to fixed time limits. Our data do not identify a single universal threshold; the optimal break point is a moderator-dependent question that requires controlled comparison. The dominant role of duration in our model still makes duration-aware adaptation a high-priority candidate intervention for follow-up evaluation.
2. **Lightweight physiological adaptation.** If physiological sensing is available in the deployment hardware, GSR-based comfort adjustment (such as field-of-view modulation, vignetting, motion-intensity reduction, or rest prompts) is a parsimonious candidate intervention that warrants controlled evaluation.
3. **Cognitive demand segmentation.** Educational content may benefit from being split into shorter, focused units with cognitive recovery periods, especially in serious-game contexts where high engagement is itself a learning objective.
4. **Individual-difference modeling.** The unexplained variance in our model points to a substantial role for individual differences. Onboarding experiences that estimate individual susceptibility, possibly via early-session physiological response, are a promising direction for personalization.
5. **Composite risk indicators for graduated adaptation.** The predictors identified here could be combined into a session-level risk score that drives graduated intervention. The efficacy of any such system still has to be established through prospective evaluation.

5.6. Implications for specific game design elements

Several aspects of our results are relevant to specific design decisions in serious-game VR.

5.6.1. Dynamic difficulty and cybersickness coupling

Our application used dynamic difficulty adjustment via Q-learning and fuzzy logic (Damastuti et al., 2024c). The cognitive-load finding suggests a candidate hypothesis: DDA systems that integrate cybersickness risk signals (such as GSR or cumulative exposure) alongside performance metrics may balance comfort and engagement better than systems that optimize performance alone. Whether this holds in practice needs a controlled comparison.

5.6.2. Passive motion in narrative sequences

Boat sequences in our application produce passive vehicle motion, which is a known potent cybersickness trigger (Reason & Brand, 1975). Because we did not analyze segment-level effects (the regression aggregates over stationary and passive-motion segments), we cannot say how much of the duration effect is driven specifically by passive motion. We hypothesize that providing visual anchoring (a stable horizon reference) or making such sequences optional would reduce per-minute symptom accumulation, and this is a direct candidate for follow-up experimental work.

5.6.3. Educational pacing

The cognitive-load finding is consistent with distributing learning content across multiple shorter sessions, particularly for novice VR users. Long single sessions with high cognitive demand are likely to be problematic, though a direct comparison with distributed-practice protocols is left for future work.

5.7. Limitations

The following limitations apply to the present work.

5.7.1. Cross-sectional observational design

The design identifies predictors, but it does not allow causal inference. We have therefore framed the design implications as testable hypotheses rather than as evidence-based prescriptions. Experimental manipulation of duration, cognitive load, or autonomic state would be needed to evaluate causal effects.

5.7.2. Single-item severity outcome

We used a single-item 10-point severity rating rather than the full Simulator Sickness Questionnaire (Kennedy et al., 1993). This choice was motivated by participant burden and the analytic goal (Section 3.5.1), but it limits construct breadth. We cannot recover predictor patterns specific to the nausea, oculomotor, or disorientation subscales, and prior work has shown that these subscales can differ in their physiological signatures (Kim et al., 2005). Subscale-level prediction with the full SSQ is a specific direction for follow-up work.

5.7.3. Session duration endogeneity

Session duration varied with voluntary engagement (Section 3.6) rather than under experimental control. Two interpretations of the duration effect are mutually consistent with the data. The first is that longer cumulative exposure produces greater symptom accumulation, which is the standard causal account supported by experimental work (Saredakis et al., 2020). The second is that participants with lower susceptibility tolerated longer sessions and accumulated more sickness as a downstream consequence. The two are not mutually exclusive, and our cross-sectional design cannot adjudicate between them. We have framed the directional interpretation of duration in Section 4.3 conservatively to reflect this concern, and we list experimental manipulation of duration as a priority for follow-up work.

5.7.4. Raw session means without baseline correction

Physiological predictors entered the regression as session-mean values, not as baseline-corrected change scores. Baseline values were recorded for sensor verification (Section 3.5.2) but were not retained in the analytic dataset, so we could not compute change scores after the fact. Inter-individual variability in resting autonomic activity is therefore partially confounded with our session-level effects. Future work that uses baseline-corrected change scores or within-participant repeated measures would partially address this limitation.

5.7.5. Single VR application and stimulus profile

All data come from one serious-game application with a specific stimulus profile that combines stationary first-person interaction with scripted passive-vehicle motion (Section 3.4). The aggregate regression cannot separate predictor effects during stationary segments from those during passive-motion segments, and generalization to other VR genres, locomotion schemes, or hardware platforms requires explicit replication.

5.7.6. No motion sickness susceptibility measure

We did not administer a validated susceptibility instrument such as the Motion Sickness Susceptibility Questionnaire (MSSQ) (Golding, 1998). This limits our ability to model individual differences as a moderator.

5.7.7. Prior VR experience uncontrolled

Our exclusion criteria addressed prior experience with the specific application, but we did not collect general VR experience beyond that. General experience moderates cybersickness susceptibility through habituation effects.

5.7.8. Single-item cognitive-load measure

Cognitive load was measured with a single ordinal three-level self-report item rather than a validated instrument such as the NASA-TLX. This limits the precision of the cognitive-load coefficient and is worth replacing in future work.

5.7.9. Mild heteroscedasticity

The Breusch–Pagan test indicated possible mild heteroscedasticity (Section 4.4). This does not affect the consistency of the OLS estimates, but inferences for borderline coefficients (in particular HR at $p = .052$) should be interpreted with the appropriate caution.

5.7.10. Laboratory setting

The controlled laboratory environment differs from typical consumer VR use. Field studies would improve ecological validity, particularly for design implications that target at-home serious-game deployments.

5.8. Future directions

A number of directions follow from this work.

1. **Prospective adaptive-system evaluation.** Build and run controlled evaluations of VR systems that use the predictors identified here as inputs to real-time interface adaptation, comparing adaptive interfaces against fixed-comfort baselines on prospective cybersickness outcomes.
2. **Experimental manipulation of identified predictors.** Run controlled experiments that independently manipulate session duration, cognitive load, or autonomic state to evaluate causal contributions and to set intervention thresholds.
3. **Subscale-level prediction using the full SSQ.** Replicate this study with the full Simulator Sickness Questionnaire to see whether the predictor pattern differs across the nausea, oculomotor, and disorientation subscales.
4. **Segment-level analysis of passive-motion contributions.** Use within-session segmentation of stationary and passive-motion exposure to quantify the per-minute contribution of passive-vehicle sequences to symptom accumulation.
5. **Personalized models that incorporate susceptibility and prior experience.** Develop individual-difference models that include validated susceptibility measures (such as MSSQ) and general prior VR experience as moderators of the relationships reported here.

6. **Cross-platform and cross-genre replication.** Replicate across VR genres, locomotion schemes, and hardware platforms to evaluate generalization beyond the specific stimulus profile of the present application.
7. **Longitudinal habituation.** Use repeated-exposure designs to evaluate how predictor relationships shift with habituation, which is directly relevant to repeated-use serious-game contexts.

6. Conclusion

We evaluated a small, theory-mapped set of physiological and cognitive–experiential predictors of cybersickness severity in a free-play VR serious-game context. The full multivariate model explained 35.8% of the variance in cybersickness severity, with session duration, GSR, and cognitive load as significant predictors. Heart rate was marginal in the full sample and became conventionally significant in the influence-diagnostic sensitivity refit ($R^2 = .426$). HRV contributed bivariately but was attenuated in the multivariate model. The directional pattern of predictors was robust across the full-sample, sensitivity, and bivariate analyses. We present these results as a comparative effect-size estimate for theory-mapped predictors in ecological serious-game VR, complementing existing predictive work on controlled stimuli.

Two practical implications stand out. First, GSR was the most consistent autonomic signal across our analyses and is therefore a sensible physiological measure to instrument first in adaptive comfort systems for serious-game VR. Second, session duration was by far the largest predictor and is the most accessible exposure-management lever available to designers. The cognitive-load effect adds a serious-game-specific concern that sets educational VR design apart from general entertainment VR. Translating these predictors into validated adaptive systems will need prospective experimental and prototyping work that goes beyond the cross-sectional design used here. We offer the comparative ranking, the theoretical mapping, and the design hypotheses reported in this study as a starting point for that translation.

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Author contribution statement

CRediT: **Fardani Annisa Damastuti**: Conceptualization, Data curation, Investigation, Methodology, Visualization, Writing – original draft; **Kenan Firmansyah**: Formal analysis, Methodology, Software, Writing – review & editing; **Yunifa Miftachul Arif**: Validation, Writing – review & editing; **Rizky Yuniar Hakkun**: Supervision, Writing – review & editing; **Mochamad Hariadi**: Project administration, Resources, Supervision.

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Data availability statement

The de-identified participant data, the analysis scripts, and the regression output that support the findings of this study are openly available on the Open Science Framework at https://doi.org/10.17605/OSF.IO/5D3E2.

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