Exploring the Attentional Cost of Visual Motion Sickness Mitigation Strategies in Smart Cabin

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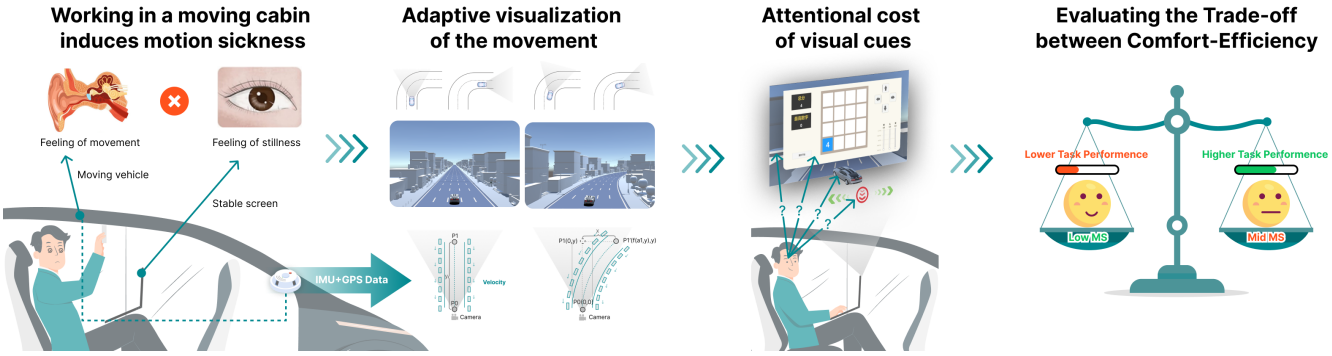


Figure 1: Exploring the Trade-off Between Visual Motion Sickness Mitigation and Attentional Cost in In-Vehicle Infotainment Systems

Abstract

Passengers are susceptible to motion sickness (MS) when engaging in non-driving-related tasks (NDRTs) in the cabin. Visual information about ego-vehicle motion can alleviate MS, yet it may also compete for cognitive resources needed for NDRTs, degrading NDRT performance. To reveal the potential negative effects of MS mitigation strategies, we designed two types of visual cues, i.e., *implicit* dynamic optic flow and *explicit* predictive symbols, and compared their MS-mitigation effects and impact on NDRT performance. An on-road driving experiment was conducted with 10 participants. Using a high-interaction NDRT, we revealed an NDRT performance degradation effect of a certain MS mitigation interface. Although all visual cues helped mitigate MS, explicit predictive cues significantly impaired task performance ($p < 0.05$), whereas implicit optic flow alone had minimal impact on NDRT performance. The results indicate that the attentional cost of MS

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mitigation cues should be carefully evaluated in the smart cabin, highlighting the need to balance sensory comfort with productivity in future intelligent cockpits.

CCS Concepts

• **Human-centered computing → Visualization design and evaluation methods**; *Empirical studies in ubiquitous and mobile computing*.

Keywords

Motion Sickness, Comfort-Efficiency Paradox, Non-Driving Related Tasks, Visual intervention, Occupant

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1 Introduction

The rise of autonomous driving has expanded the scope of Non-Driving Related Tasks (NDRTs), yet motion sickness (MS) remains a critical bottleneck for the usage of In-Vehicle Information Systems (IVIS) or bring-in devices during the ride. Characterized by symptoms such as nausea and headache [6, 9, 20], MS is primarily driven by sensory conflict—the incongruence between vestibular motion signals and visual inputs [20], and it intensifies when passengers focus on static in-vehicle screens while experiencing vehicle motions [10].

Prior research shows that providing visual cues of vehicle motion can mitigate MS [10, 25, 30], for instance, by introducing implicit motion reference frames [4, 12, 15, 17, 18] or explicit predictive cues of vehicle trajectories [2, 13, 22]. However, these two approaches differ fundamentally in how they engage attention. *Implicit* cues such as dynamic optic flow act through peripheral, low-level perception, whereas *explicit* cues such as predictive symbols require focal attention and semantic decoding. However, existing studies emphasize MS symptom reduction and largely overlook the cognitive demands of the MS mitigation strategies, so the extent to which they interfere with NDRT efficiency remains unclear. This matters, as without mitigating MS when engaging in NDRTs, passengers may not be able to make use of commuting time for work or entertainment, and the social benefit of the smart cabin and the driving automation may be compromised [14].

Therefore, to quantify the attentional cost of MS mitigation cues, we developed two MS-mitigation interfaces, one based on perception of optical flow and one based on symbolic cues. We hypothesized that the optical-flow-based MS-mitigation interface is more compatible with NDRTs that require focal vision, given that optical flow and focal vision rely on two distinct visual channels [3]. By comparing the performance of two representative NDRTs when two MS-mitigation interfaces were provided in an on-road experiment, we revealed the potential side-effects of certain MS mitigation strategies.

2 Method

2.1 Visual Interface Design

Two visual cues were designed: *implicit* dynamic optic flow and *explicit* predictive symbolic cues.

2.1.1 Optic Flow. Grounded in sensory conflict theory [20] and inspired by Qiu [19], we built an adaptive system that transforms real-time acceleration into 2D display parameters that are aligned with human perception (Figure 2), providing a coherent spatial reference that reduces sensory conflict through bottom-up processing. We modeled the lateral offset of the virtual road as a function of steering dynamics:

$$x = f(\omega, y) = g(\omega) * y^2 \tag{1}$$

where y was the longitudinal distance from the virtual camera and ω was the real-time yaw rate. To ensure smoothness and stability, $g(\omega)$ was designed as a bounded nonlinear sigmoid mapping:

$$g(\omega) * y^2 = \begin{cases} k * \sigma(z(\omega)) * y^2 = \frac{k * y^2}{1+e^{-z(\omega)}} & \omega > 0 \\ 0 & \omega = 0 \\ -k * \sigma(z(\omega)) * y^2 = \frac{-k * y^2}{1+e^{-z(\omega)}} & \omega < 0 \end{cases} \tag{2}$$

where k was a gain that controls the maximum curvature. The intermediate variable $z(\omega)$ normalized the signal into the sigmoid's sensitive range:

$$z(\omega) = \alpha \cdot \frac{|\omega| - \omega_{\text{mid}}}{\omega_{\text{range}}} \tag{3}$$

with $\omega_{\text{mid}} = (\omega_{\max} + \omega_{\min})/2$ and $\omega_{\text{range}} = (\omega_{\max} - \omega_{\min})/2$. This formulation provides three key properties:

- Perceptual sensitivity: signals within $[\omega_{\min}, \omega_{\max}]$ were mapped to the high-sensitivity region of the Sigmoid function through a scaling factor α. In this study, $\alpha \approx 5$ and mapped the effective input range to $[-5, 5]$, where the sigmoid achieved an optimal balance between responsiveness and dynamic range.
- Noise suppression: sub-threshold inputs ($|\omega| < \omega_{\min}$) produce negligible visual response. Thus, the lower bound $\omega_{\min} = 2.6^\circ/s$ was derived from human perceptual thresholds for rotational motions [1], ensuring that imperceptible signals were filtered out. The upper bound $\omega_{\max} = 10^\circ/s$ was based on naturalistic driving observations, covering typical steering dynamics while avoiding excessive visual distortion.
- Saturation control: Large inputs asymptotically approached a bounded maximum, preventing instability in visual output. The gain parameter k=0.3 was calibrated through pilot experiments to achieve perceptual consistency between visual curvature and real-world motion, effectively improving visual–vestibular congruence.

2.1.2 Predictive Symbolic Cue. Implicit optic flow may lack the efficacy required for anticipation of vehicle motion. Thus, we designed explicit predictive symbols that announce upcoming or ongoing maneuvers (Figure 3), comprising: (i) **symbolic information**—1 Hz flashing symbols in the peripheral field 3 s before a maneuver, leveraging pre-attentive processing for feedforward awareness [29]; and

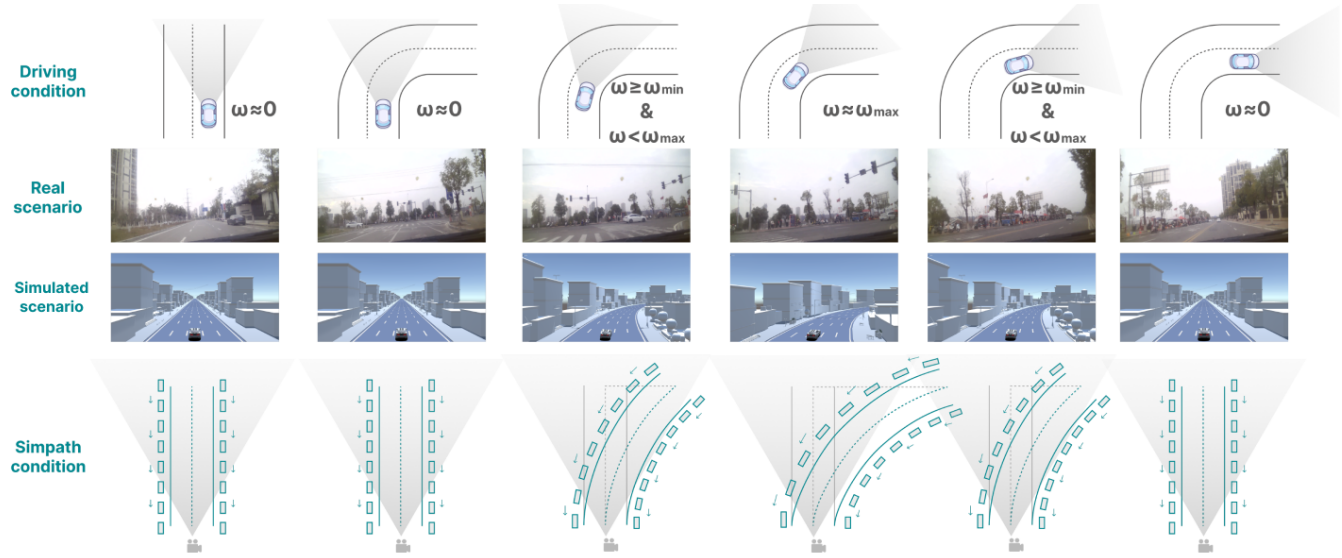


Figure 2: Adaptive visual system under different driving conditions.

(ii) **vehicular motion information**—a third-person 3D vehicle model providing a stable spatial reference [23] for lateral displacement and yaw, with the brake light activated when longitudinal deceleration exceeded 0.17 m/s^2 [1].

2.2 Participants

A total of 10 participants (7 males, 3 females), with ages ranging from 19 to 29 years ($Mean$ = 24.76, SD = 2.63) were recruited. All were pre-screened for moderate-to-high motion sickness susceptibility using the MSSQ-Short [7], and reported normal or corrected-to-normal vision with no history of vestibular or neurological disorders.

2.3 Apparatus

An IMU+GPS sensor (Weite Intelligence WTGAHRS2) was mounted at the front of the test vehicle to log vehicle dynamics. A 15.6-inch touchscreen (3840 × 2160) behind the driver's seat presented the NDRT and the MS mitigation cues. A curtain obscured the front and side windows to enhance MS effects and remove external visual references. The test vehicle was a Geely Emgrand L, and the interface was implemented in Unity. The route and in-vehicle setup are shown in Figures 4.

2.4 Non-Driving-Related Task

Grounded in multi-dimensional task-attribute theory [8] and prior research [24], we adopted a high-interaction cognitive task. The 2048 Game is a tile-sliding puzzle that requires players to merge tiles with the same number on a 4×4 grid to reach the 2048 tile. Whenever two tiles are merged, a new tile with a number of 2 (70% chance) or 4 (30% chance) would appear. It heavily recruits the visuo-spatial sketchpad and the central executive for rapid decision-making, requiring continuous visual attention and hand–eye coordination. Performance was quantified by game scores (i.e., the sum of all numbers in the grid).

2.5 Experimental Design and Procedures

A within-subject design was used: each participant experienced all four visual conditions—*Baseline*, *predictive-symbolic-cue-only* (explicit), *optic-flow-only* (implicit), and the *combined* conditions (Figure 6).

After signing a consent form and receiving training, participants completed the experimental trials with four visual conditions (see Appendix for orders of experimental conditions). Before and after each trial, they filled out the Simulator Sickness Questionnaire (SSQ) [11]. A minimum 30-minute rest separated trials until subjective MS ratings returned to baseline (i.e., SSQ of 0), to prevent fatigue and habituation. The experiment was conducted on road (~9.8 km, ~40 km/h; Figure 5), including straight segments, turns, and traffic lights to ensure ecological validity. In total, 40 trials were collected (10 participants × 4 conditions)(Figure 6).

2.6 Dependent Variables and Statistical Models

Two dependent variables were measured. **Task performance** was the 2048 game score. **MS** was assessed by the post-trial SSQ, categorizing symptoms into nausea, oculomotor, and disorientation. A one-way repeated-measures analysis of variance (ANOVA) was conducted separately for post-trial SSQ and NDRT performance to examine the main effect of visual condition. Significant omnibus effects ($p < .05$) were followed by paired-samples t-tests with Holm adjustment for multiple comparisons.

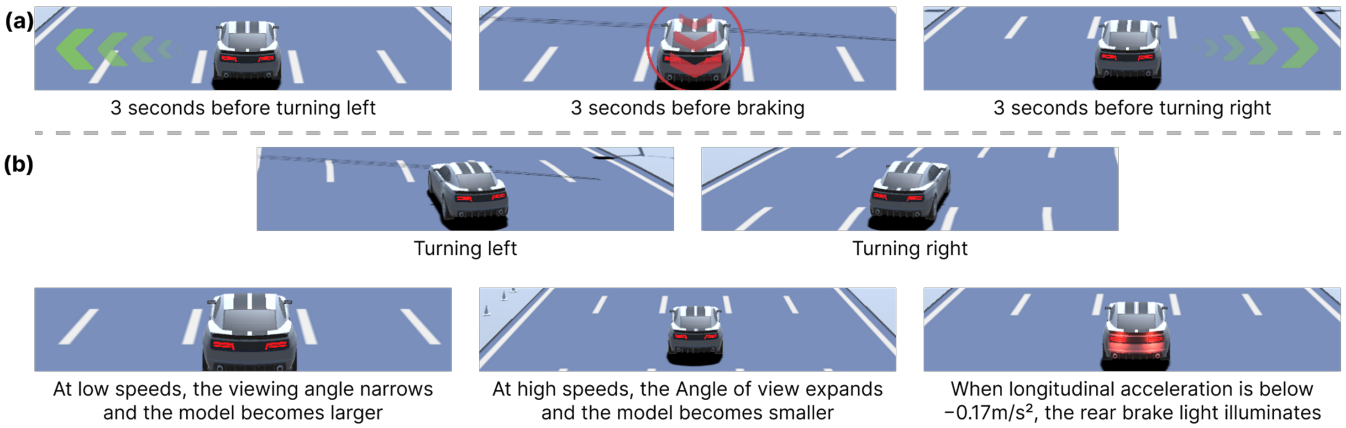


Figure 3: (a) 1 Hz flashing symbols; (b) Third-person 3D vehicle model.

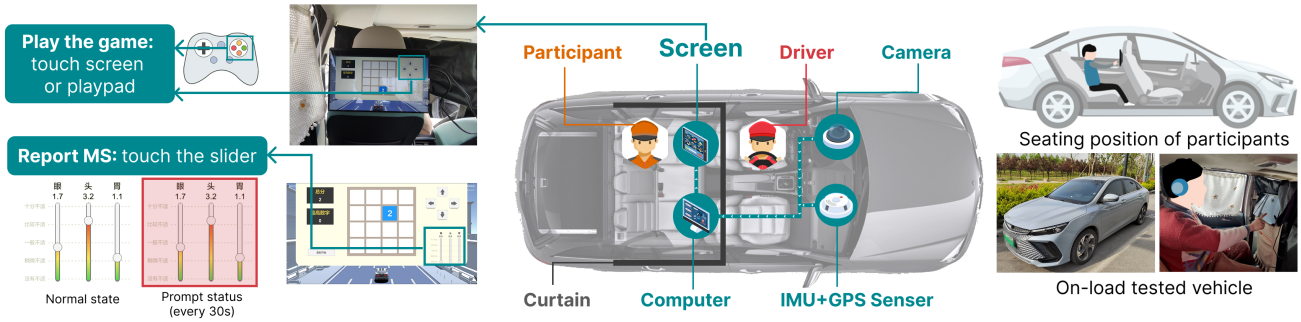


Figure 4: Interior layout of the vehicle and Apparatus.

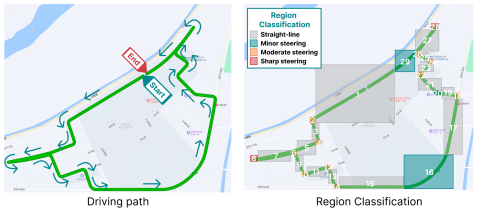


Figure 5: Road condition and regional information.

3 Results

3.1 MS Mitigation

Visual condition significantly affected Post-SSQ scores(Figure 7a). The repeated-measures ANOVA revealed a significant main effect of visual condition, $F(1.88, 16.90) = 12.18$, $p < .001$, $\eta_p^2 = .575$. Holm-adjusted paired comparisons showed that the Baseline ($M = 89.76$, $SD = 20.94$) produced significantly higher SSQ scores than the predictive-symbolic-cue-only condition, $t(9) = 3.56$, $p = .03$, with an estimated difference Δ of 19.07, and 95% Confidence Interval (95%CI) of [6.95, 31.20]. At the same time, Baseline also led to higher SSQ score than the optic-flow-only condition, $t(9) = 4.42$, $p = .008$, $\Delta = 12.34$, 95%CI: [6.03, 18.65], and the combined condition, $t(9) = 7.14$, $p < .001$, $\Delta = 26.55$, 95%CI: [18.15, 34.96]. No other significant differences were observed ($p > .05$).

3.2 NDRT Performance

Visual condition significantly affected game performance(Figure 7b), $F(3, 27) = 3.11$, $p = .04$, $\eta_p^2 = .257$. Holm-adjusted paired comparisons showed that the optic-flow-only condition significantly outperformed the combined condition, $t(9) = 4.68$, $p = .007$, $\Delta = 324.8$, 95%CI [167.9, 481.7] and the predictive-symbolic-cue-only condition, $t(9) = 3.11$, $p = .01$, $\Delta = 315.0$, 95%CI [85.9, 544.1]. No other significant differences were observed ($p > .05$).

3.3 Correlation Analysis between NDRT Performance and MS

Pearson correlation (Figure 7c) revealed no significant relationship between post-trial SSQ and task performance ($r = 0.201$, $p = .2$), indicating that the performance decline cannot be solely attributed to MS itself. Instead, explicit cues introduce additional attentional demands that interfere with task execution.

4 Discussion

In this on-road study, we examined the potential negative effects of visual MS mitigation strategies when passengers engaged in a high-interaction NDRT. First, it is not surprising that all MS mitigation

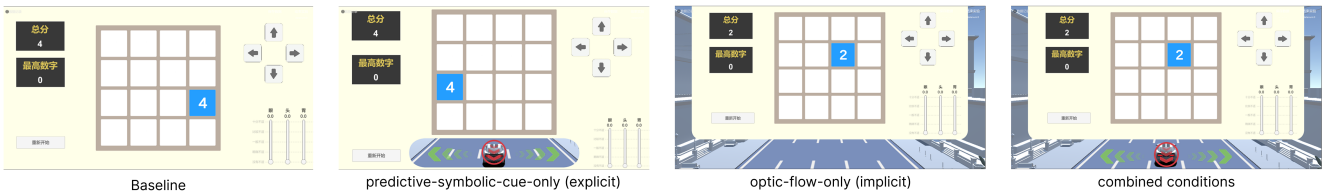


Figure 6: Interfaces used in this experiment.

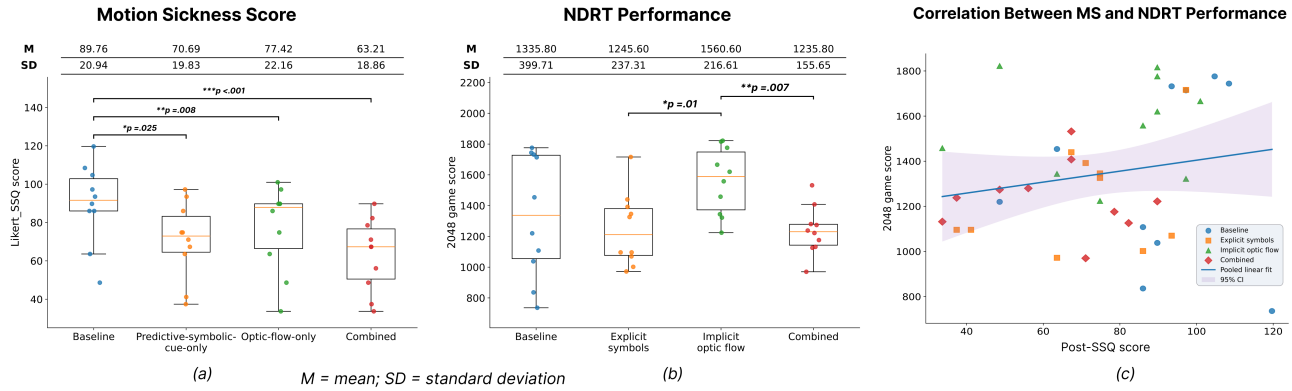


Figure 7: Data analysis: (a) MS value (Post-SSQ score); (b) NDRT performance (2048 game score); (c) Scatter plot of MS and game score. Significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

strategies have successfully mitigated the MS in our experiment. All strategies facilitated **sensory alignment** by mapping real-time acceleration into motion-consistent optic flow or predictive information, reducing the visual–vestibular mismatch that can lead to MS. Such an effect of visual motion cues has been widely explored in previous studies (e.g., [4, 12, 17, 18]). Our study further showed that both bottom-up (optic flow) and top-down (predictive symbolic cue) ways of providing the vehicle motion information can effectively mitigate MS to a non-distinguishable level, though readers should be cautious about our sample size.

Further, we found that while effective for MS mitigation, the explicit cues (predictive symbolic cue) imposed a higher cost than the implicit cues (real-time optic flow) [28]. Further analysis indicated that the performance decline may be more likely to be due to competition for limited attentional resources than to discomfort itself, because MS severity was not found to be correlated with task performance. This is as expected, as predictive symbolic cues require focal attention and semantic processing, which may compete with the NDRTs that claim similar resources [24, 27], whereas optic flow can be processed peripherally [21]. More specifically, decoding the direction, timing, and meaning of explicit symbols engages largely sequential executive control that interferes with the ongoing NDRT. Similarly, the combined condition also claimed similar types of cognitive resources as the predictive symbolic cue condition. In addition to the resource competition, the transient symbols may also act as visual distractors [26], triggering frequent task switching [28] and disrupting cognitive continuity. Implicit optic flow, processed peripherally, may have avoided this cost and distracting effect.

4.1 Limitations and Future Work

Several limitations should be noted. First, the 2048 game is a high-load proxy rather than a standard task and does not fully capture real in-cabin interactions, so generalization of the finding needs to be further validated. Second, the study had a small sample size ($N = 10$) with limited route diversity. Future research should validate our findings with a larger sample size in more diverse traffic. Third, only subjective MS ratings were used in our study; given that the NDRTs and the cues were all visual, future work should incorporate eye-tracking measures to quantify drivers' attentional allocation strategies [16]. Future research can also consider physiological metrics, such as electrogastrography [5], as the ground truth of MS levels. Finally, we only considered two different visual MS-mitigation cues. Future research should also map an "efficiency–comfort" curve by systematically varying visual elements in the cues, such as contrast and lead time. Beyond visual cues, multimodal countermeasures that distribute information across sensory channels should also be investigated. For example, auditory [31] and vibrotactile [13] cues may also improve passengers' awareness of upcoming vehicle motion without occupying focal visual attention.

4.2 Conclusions

In summary, for the first time, this preliminary study examined the "side effects" of visual MS-mitigation in an on-road experiment. Overall, our findings reveal that strategies that mitigate MS may also negatively affect NDRT performance. Thus, future MS-mitigation interfaces in the cabin should shift from "singular comfort metrics" to "dynamic efficiency balancing", for example, by prioritizing implicit optic flow for high-interaction, high-immersion tasks (e.g., gaming, office work), and reserving explicit symbols for low-interaction tasks (e.g., reading, watching).

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A Order of Experimental Conditions

The order of the four visual conditions: Baseline (B), predictive-symbolic-cue-only (P), optic-flow-only (O), and the combined condition (C), and the gender of all conditions: Male(M), Female(F) We tried to balance the orders among the 10 participants.

Table 1: Experimental condition orders.

Participant	Gender	Trial 1	Trial 2	Trial 3	Trial 4
1	M	B	P	C	O
2	M	P	O	B	C
3	M	O	C	P	B
4	F	C	B	O	P
5	M	B	P	C	O
6	M	P	O	B	C
7	F	O	C	P	B
8	F	C	B	O	P
9	M	B	P	C	O
10	M	P	O	B	C