# Allocation of Fixational Eye Movements in Response to Uncertainty in Dynamic Environments

**Nikita Abalakin[1,3,*], Nils Wendel Heinrich[1,4,*], Annika Österdiekhoff[2], Stefan Kopp[2], Nele Rußwinkel[1]**
abalakinikita@gmail.com
[1]Institute of Information Systems (IFIS), Department of Computer Science and Engineering, Universität zu Lübeck, Lübeck, Germany
[2]Social Cognitive Systems, Faculty of Technology, CITEC, Bielefeld University, Bielefeld, Germany
[3]Department of Psychology, University of Potsdam, Potsdam, Germany
[4]Cognitive Psychology and Ergonomics, Technische Universität Berlin, Berlin, Germany
*These authors contributed equally to this work

**Abstract**

The complexity and unpredictability of a situation might contribute to how much an individual feels in control of their actions. Goal-directed behaviour tailored to different situations is enabled through a hierarchy of situated action control combining cognitive and sensorimotor control processes. We use eye-tracking to investigate the grounding of cognitive processes in the sensorimotor system. Our assumption is that different degrees of perceived control trigger cognitive states that are reflected in eye-movement behaviour. Utilizing a dynamic experimental environment, we investigate whether complexity and uncertainty of the situation are top-down processed into fixational eye movements. The distance to a reference point is affected by environmental complexity in all fixations; however environmental uncertainty is only incorporated in fixations that guide motor control. We discuss that these fixations are only executed under high sense of control when there are enough cognitive resources left to top-down process the environmental uncertainty into gaze allocation.

**Keywords:** situated action control; visual attention; eye-movement control; sensorimotor grounding

## Introduction & Theoretical Background

Although many aspects of a motor action occur without awareness, being aware and in control of an action is one of the most essential components of conscious experience (Blakemore & Frith, 2003). Surprisingly, the awareness of an intended movement does not necessarily mean that this exact movement will be performed. However, the match between intended and performed actions is what makes individuals take ownership of their actions. Therefore, the timing, trajectory and precision of the action are essential aspects of movements for people to be aware of how they interact with the outside world. The predicted effect the movements would have on the sensory feedback is the action-perception loop that is the centre of almost every model of action-awareness.

It becomes clear why prediction is such a critical aspect of being aware of the movement (Synofzik et al., 2013). The better the prediction, the more one feels in control of an action. But when there is a mismatch between the prediction and what actually happened, another aspect comes into play, called postdiction, where the individual tries to adjust the action to minimise this mismatch. In the sensorimotor-based comparator model of action awareness, Synofzik and colleagues (2008) suggest that if sensorimotor prediction and sensory feedback align, it leads to feeling in control of an action. On the basis of this, further models were developed which predict that the actions that are most likely to match the prediction are selected (Kahl et al., 2022). Therefore, the feeling of control loss is accounted for in the action selection process, in which the action intentions are selected that have a higher chance of being implemented as predicted.

Visual feedback might be one of the most accurate sensory channels to identify a mismatch. Consequently, the cognitive processes underlying action selection and pursuing selected action intentions are grounded in oculomotor control. Therefore, we investigate changes in eye-movement behaviour while introducing various types of uncertainty in an experimental computer game environment. When the outcomes of actions are harder to predict, it will lead to a feeling of control loss and thus to changes in action selection. We expect that the allocation of fixational eye movements might reflect the cognitive state of control loss that leads to these changes in oculomotor control. More specifically, we hypothesize that the feeling of control loss leads to eye-movement control being based on the properties of the visual field (e.g. properties of stimuli) rather than higher cognitive processes such as task-relevant planning or the like.

### Visual Attention & Oculomotor Control

In attention control models, two main accounts for directing attention are discussed: *stimulus-based control* and *goal-driven control* (Vecera et al., 2014). The stimulus-based control, also called bottom-up control, involves the allocation of attention based on the salience of an object or a region in the visual field. Here, the optical characteristics of an object, such as size, colour, or motion, drive attention allocation. On the contrary, goal-driven control, also called top-down control, allocates attention on the basis of the individual's intentions. Attention allocation in this case is mainly driven by task requirements and task-relevant stimuli. How individuals process and prioritize visual information lies in understanding the interplay between these two control modes. Vecera and colleagues (2014) point out that although stimulus-based attention control is thought of as the default one, in real-life behaviour, goal-driven is the more frequently used mode.



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Our oculomotor behaviour is highly specialized, executing distinct eye movements in response to various tasks (Land & Hayhoe, 2001). This becomes particularly evident when reading (e.g. Vitu & McConkie, 2000), or engaging in dynamic tasks such as driving (e.g. Broadbent et al., 2023) or playing computer games (e.g. Holm et al., 2021). Specifically, tasks that are solved within dynamic environments, environments that change constantly over time and are clustered with uncertainty require efficient eye-movement control to aid goal-directed behaviour. Our visual system is tuned to identify action possibilities (Gibson, 1966). The top-down processing component of eye-movement control factors in the various options to act within a given environment. But what happens when the environment is increasingly uncertain (and complex) that action possibilities to solve the task at hand become difficult to identify? According to the assumptions of Vecera and colleagues (2014), the allocation of attention via eye-movement control should be based less on top-down processing and more on the visual properties of the environment (bottom-up control).

We aim to investigate this exact interplay of stimulus-based and goal-driven control of visual attention by combining a dynamic environment, in which participants solve a continuous task, with eye tracking. This should allow us to identify properties of eye movements that stem from bottom-up or top-down control, respectively.

**Previous Findings**

Mallic and colleagues (2016) investigated several eye metrics to estimate cognitive states such as workload and fatigue. Participants played a Tetris game with increasing speed of falling blocks, which would increase cognitive load. The number of fixations increased while fixation durations decreased as the task became more difficult. Furthermore, the cognitive load in driving also affects oculomotor behaviour (Mahanama et al., 2022). A study of multi-tasking during driving revealed that the number of fixations in a single-task condition (driving only) was significantly higher than in a dual-task condition (driving and auditory task; Broadbent et al., 2023). In a study with self-driving cars, during expected stops, participants fixated more and longer on the human-machine interface as opposed to the central or the peripheral environment (Stephenson et al., 2020). When the stops were unexpected, fixations were placed upon the central environment longer and more frequently. This implies a demand on attentional resources during unexpected events and that attention is then directed towards what is in front of the agent, in front of the car. Unexpected events in a study about a first-person shooter videogame elicited a higher number of fixations and decreased fixation durations (Holm et al., 2021). In this study, however, the unexpected events were associated with less central vision. During these events, players stayed relatively still while exploring the visual field. This is in line with findings indicating that scenery change is associated with higher visual motion (Zacks et al., 2006).

Another spatial factor in fixations pertains to the control of an agent in a dynamic environment. For example, in driving research, novice drivers prefer to fixate on road points that might help with steering (Robbins & Chapman, 2019). In contrast, experienced drivers shifted their gaze away from these helpful points and explored the visual field more horizontally.

Looking at these previous findings, it becomes clear that differences in the characteristics of eye-movement behaviour are caused by different types of uncertainty. These may be because someone is still a novice at performing a task, or because various events could not be anticipated, or because processing bottlenecks led to a higher cognitive load. In the present study we try to understand the different control mechanisms that affect eye-movement control. Therefore, we apply high-frequency eye-tracking and combine it with the Dodge Asteroids experimental environment (Heinrich et al., 2023), in which participants steer an agent within a dynamic environment.

We take into account that individual fixations can be executed on the basis of a variety purposes. Hence, we resort to distance to reference point (D2R) for categorizing different fixational eye movements. D2R is a computation of the Euclidian distance from the fixation to the AOI (Falck-Ytter et al., 2013). More specifically, we make a distinction between *close fixations* and *distant fixations*. Close fixations are fixations made while the agent or a reference point is inside the region of central vision (fovea and parafovea; up to 5° eccentricity) and thus can be perceived with relatively high accuracy. Fixations made with the agent being outside of the central vision region, in peripheral vision, are referred to as distant fixations. In these cases, we assume that the gaze is detached from the reference point to such an extent that the environment and not the agent's immediate surroundings are visually explored. Distant fixations might serve guiding other manual control, foveating on future locations for example of hands in grasping movements or the vehicle when driving.

The main objective of this study is to investigate changes in visual exploration induced by situations of various uncertainty. For this, we assess gaze allocation relative to the agent as key metric for visual exploration in both types of fixations individually (close and distant fixations). We assume that the distance to the agent that participants control within the Dodge Asteroids environment reflects the feeling of control at the cognitive level. Despite the exploratory nature of the study, based on previous findings, we expect that the *distance to the agent* is *smaller* in situations of *higher unpredictability* and *higher complexity*. We anticipate this to be true for both types of fixations. A short distance therefore implies lower control. In close fixations allocating the gaze even closer to the agent might signify having to monitor the outcome of each motor command with higher accurate vision. On the contrary, in distant fixations shorter distances might imply the pursuit of action intentions that are more easily to accomplish. This is consistent with previous results of novice and expert drivers where, compared to the experts, novice drivers execute fixations that are allocated closer to the vehicle (Robbins & Chapman, 2019).

## Methods

### Participants

Participants were recruited through the SONA-Platform and were students at the University of Potsdam. The recruitment process was conducted from June 1st, 2023, until June 15th, 2023. Overall, twenty adults ($N_{female}$ = *15*) with a mean age 23.57years ($SD_{age}$ = 4.89years) took part in the experiment. All participants provided written informed consent and were either financially compensated (12€/hour) or collected participant hours. A vision test was conducted to assess the normality of each participant's vision. The correction to normal was allowed only with help of contact lenses, as a reflection from glasses could compromise eye-tracking data.

### Experimental Paradigm

We adapted the Dodge Asteroids environment (Heinrich et al., 2023), a game-like experimental environment, implemented in Python (Van Rossum & Drake, 2009) using the PyGame package (Shinners, 2011) that runs at 60 frames per second. In every trial of the experiment, participants have to steer an *agent* (green spaceship visible in Figure 1A) to a finish line by staying inside borders and avoiding *obstacles* (comets). The spaceship automatically travels downward in the environment, but participants can control the spaceship horizontally. On the screen, however, the spaceship is stationary at X = 954, Y = 270 position to remain a fixed reference point. Steering will thus result in the surroundings moving around the spaceship.

To fully understand the experimental design, clarification of the terms is needed. The length of the environment and exact positions of the comets and are defined as a *level*. As a *run*, we define the manipulations of one level. Thus, playing one level with and without comets would sum up to two runs. The grouping of all levels with the same manipulation is defined as a *block*. For example, an easy block would mean all levels in condition are played with runs with a fever number of comets (N_easy). A single attempt to steer the spaceship to the finish line at the bottom of the level is defined as a *trial*. Every participant has a maximum of 3 attempts per run. If all three attempts for a given run are unsuccessful, this specific run is removed from the experimental procedure.

In order to investigate the oculomotor behaviour in an environment with different types of uncertainty, we introduce the *drift* manipulation. Within the environment, drifts are visualised as red bars. In the normal drift condition, upon entering the area on the Y-axis occupied by the red bar, in every frame the agent is pushed to the opposite side of the red bar by half of a normal step if steered (Figure 1A). Different types of uncertainty result from manipulating the visual appearance of drifts. In addition to normal drift as described above (visible as red bar and imposing movement to the opposite side of half a normal step size), two new drift conditions are introduced: *fake drifts* and *invisible drifts*. The fake drifts appear as a red bar, the same way as the normal drifts, but no horizontal movement is applied to the agent; thus, the drift does not affect the spaceship's position within the environment. The invisible drifts are not visually displayed in the game, but they have the same effect as the normal drifts, pushing the agent to the opposite side of the drift bar by half a step size.

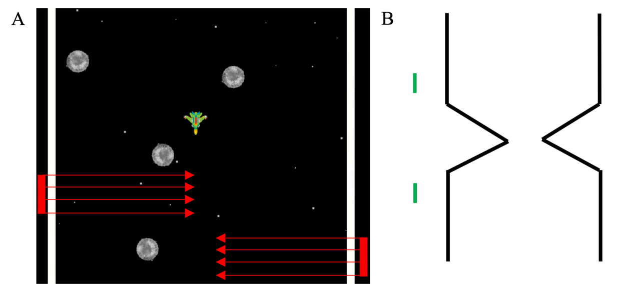


Figure 1: A. Visualization of an instance within a run in the Dodge Asteroids environment with red arrows symbolising the directional effect of drift; B. Graphic representation of the drifts in a level. Drift constellation A in red, drift constellation B in green. The colours are for visualisation purposes only. All tiles in the game remain red.

In the experiment, there are three blocks. In every trial of a block, half of the drifts are always normal drifts. The other half differs from block to block and will be either no drifts referred to as *normal* block), fake drifts (referred to as *fake block*, and invisible drifts (referred to as *invisible block*). Overall, 6 levels with the same number of comets (N) and the same length (750 vertical steps) are played. Each level features 8 drifts, whereas each drift is randomly assigned to one of two constellation groups, A and B (depicted as green and red in Figure 1B). There are 2 variations of each level to prevent the effects of specific drifts within the level and ensure the same conditions for each drift manipulation. In variation 1, all drifts belonging to group A are applied as normal drifts, and all drifts belonging to group B are manipulated drifts according to the block. The opposite is true for variation 2, where all drifts belonging to group A are manipulated drifts according to the block, and all drifts belonging to group B are applied as normal drifts. See Table 1 for an overview.

Table 1: Variations of drifts in the blocks

| Normal | Fake | Invisible |
|---|---|---|
| A – Normal | A – Normal | A – Normal |
| B – No Drift | B – Fake | B – Invisible |
| A – No Drift | A – Fake | A – Invisible |
| B – Normal | B – Normal | B – Normal |

This means that every drift is experienced as a normal drift as well as a manipulated drift. This choice in experimental design together with a maximum number of attempts is intended to prevent participants from remembering certain drift situations. Every level is played with each of the three different drift manipulations in both constellations A and B, therefore each level is played at least 6 times (given that the run was successfully completed in the first attempt). Therefore, in total, at least 36 runs (6 levels x 3 blocks x 2 variations) are played. If a player crashes into a wall or obstacle during a run, they are stripped of an attempt and the run is inserted at a random position within the sequence of the block. This means a participant can play a maximum of 108 trials during the experiment.

In the experimental procedure, the normal block is always the first block that is presented. After that, one of the manipulation blocks (fake/invisible) is presented. The order of the manipulation blocks is counterbalanced across participants. Between the two manipulation blocks, levels with normal drift condition are inserted to re-establish baseline behaviour.

## Eye-tracking Procedure

Participants eye movements were recorded binocularly using the ViewPixx TRACKPixx eye tracker (VPixx Technologies, Saint-Bruno, QC, Canada) with a sampling rate of 2000 Hz. The eye tracker recorded X- and Y-coordinates of the individual eyes. The task was presented using a 28” ASUS PB277Q screen with a 60 Hz refresh rate. Participants sat at a distance of 70 cm away from the screen, and the camera was positioned just below the screen. Participants were asked to place their heads on a chin rest and remain in this position during trials. Before the start of the experiment, participants had to complete a nine-point calibration to ensure tracking accuracy. Before each trial, an additional five-point calibration was performed. Participants were asked to keep their gaze on the screen while playing. After every trial, participants were allowed to leave the chin rest and look at a keyboard to rate their control over the spaceship.

Every row of the eye-tracking data obtained corresponds to a single fixation. Each fixation is associated with participants’ ID, block type, drift variation, drift type, trial, number of drift tiles on screen (visible or not), number of visible obstacles, and its location given by the midpoint of X- and Y-coordinates of both eyes. The data set also includes the Euclidean distance to the spaceship given in visual degrees, fixation duration, fixation count (how many fixations were executed before in this given trial).

To adjust the eye tracker and familiarize participants with gameplay and controls, three levels with varying numbers of comets were played as training before the start of the actual experiment. These training runs were played without drifts to avoid potential learning effects for drift. The experiment was terminated if a participant could not finish all three training runs within three attempts each. Participants were still compensated for the time they contributed.

Overall, one experiment session took a maximum of 90 minutes to complete. No sensitive data was collected, and participants were given enough time for breaks. Therefore, this study aligns with ethical guidelines common in psychological research.

## Data Analysis

To analyze the eye-tracking data, we applied linear mixed-effects models (LMM) in R (version 4.3.0) using the lme4 package (Bates et al., 2015). LMMs are a powerful statistical tool for analyzing data with fixed and random effects (Gałecki & Burzykowski, 2013). Fixed effects are variables that are considered to be a factor of interest and have a direct effect on the dependent variable. In contrast, random effects are used to model the variability across different groups or individuals, allowing to account for effects on group- or subject-level. The intent of the analysis is to derive two individual mathematical models that predict the distance to agent. One for close fixations in which the agent is within parafoveal vision (distance between point of fixation and agent is less than 5 visual degrees) and distant fixations (point of fixation being at least 5 visual degrees away from agent). Based on a box-cox analysis (Box & Cox, 1964), the distance to the spaceship was logarithmically transformed. Note that all reported estimates of effects are therefore on the logarithmic scale.

### Fixed Effects

*Block type, number of drifts,* and *number of visible obstacles* are included in the models as fixed effects. The number of drifts (ND) corresponds to the number of drift tiles present on screen (visible or not) during the time of initiation of the fixation. The number of visible obstacles (NVO) corresponds to the number of comets visible on the screen at the time of initiation of the fixation.

The normal block is chosen as a baseline condition. NVO and ND are continuous variables and left uncentered, as the intercept is interpretable with no drifts and no comets on the screen. Therefore, the intercept in all models represents the mean value of a dependent variable in the normal block with no comets and no drifts.

We assume an interaction between the block type and ND. These two variables represent the environmental uncertainty for participants. NVO represents the complexity of the environment at that specific moment in which the fixation is executed.

Bootstrap estimates of confidence intervals are obtained to achieve more generalizable parameter estimations. Individual parameters are re-sampled, and 95% confidence intervals are reported. A total of 5000 re-samples are used for each of the two models.

### Model Selection

Random effects are chosen for each model individually by comparing different random effects structures. To generalize results over various populations, the intercept will vary by participant due to the assumption that the individual differences across participants might contribute to the overall variance of the results. It is also assumed that individual differences contribute to the variability of responses to the various block types. Therefore, we introduce a random slope effect for block type. The models that do not converge or have a singularity issue, which can be caused by overfitting the random-effects structure, are not included when selecting the final model. The random effects structure is chosen by referring to the Bayesian Information Criterion (BIC; Chakrabarti & Ghosh, 2011). The BIC prioritises simpler models over complex ones, therefore it is used to identify the most correct model with the highest chance of being reproducible, aiding further implementations of the experiment.

# Results

## Learning Effect

A logistic LMM is fitted to predict the probability of successfully completing a trial to investigate possible learning effects. Block progression signifies the percentual completion of a specific block. We found a main effect for block progression (*OR* = 1.02, *SE* = 1.01, *p* = .005, *95% CI* [1.01, 1.03]). The fake block condition significantly differs from the normal block, which was coded as baseline (*OR* = 3.8, *SE* = 1.58, *p* = .004, *95% CI* [1.7, 9.27]). The effects of block progression on success probability can be seen in a figure 2.

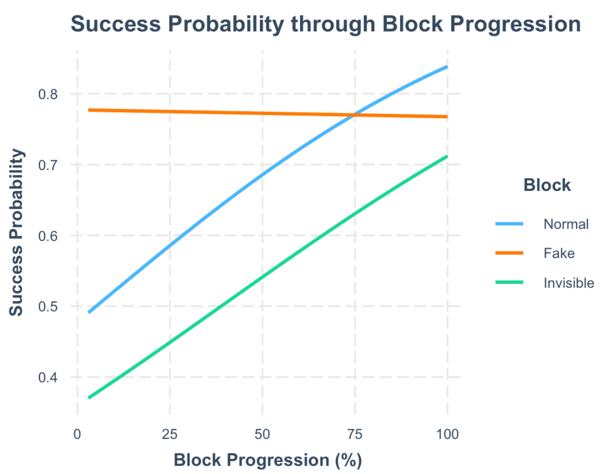


Figure 2: the change in probability of completing a trial with increasing block progression.

## Close Fixations

The final model to predict fixation distance to ship in close fixations includes a random intercept effect for participant ID and a random slope effect for block type (*BIC* = 80661). Table 2 provides an overview of all effects for this model. We found a significant main effect of NVO (*b* = .01, *SE* = .001, *p* <.001, *95% CI* [.01, .015]), indicating that the distance to the spaceship increases with increasing NVO. The block types do not significantly differ from each other. The interaction between the fake block and ND is approaching significance (*b* = .003, *SE* = .02, *p* = .055, *95% CI* [0.0, .07]).

Table 2: Parameters for distance to spaceship in close fixations

| Effect | Estimate | *SE* | 95% CI | | *p* |
|---|---|---|---|---|---|
| | | | *LL* | *UL* | |
| Intercept | 0.81 | 0.06 | 0.69 | 0.93 | <.001 |
| NVO | 0.01 | 0.001 | 0.01 | 0.015 | <.001 |
| ND | -0.01 | 0.02 | -0.03 | 0.02 | .70 |
| FB | -0.01 | 0.04 | -0.09 | 0.06 | .72 |
| IB | -0.05 | 0.03 | -0.11 | 0.01 | .10 |
| ND x FB | 0.03 | 0.02 | 0.0 | 0.07 | .05 |
| ND x IB | 0.03 | 0.02 | -0.02 | 0.06 | .06 |

*Note.* FB – Fake Block; IN – Invisible Block.

## Distant Fixations

Similar to the one for close fixations, the final selected model to predict the distance to the spaceship in distant fixations includes a random intercept effect for the participant ID and a random slope effect for the block type (*BIC* = 35951). For an overview of all effects for this model, see table 3. NVO significantly affects the predicted variable (*b* = -.02, *SE* = .001, *p* <.001, *95% CI* [-.02, -.01]), indicating shorter distances to the spaceship with increasing NVO. The main effect of ND is significant (*b* = -.04, *SE* = .01, *p* <.001, *95% CI [-.06, -.02]),* also eliciting shorter distances with increasing ND. There are no significant effects for block type or the interactions between block type and ND.

Table 3: Parameters for distance to spaceship in distant fixations

| Effect | Estimate | *SE* | 95% CI | | *p* |
|---|---|---|---|---|---|
| | | | *LL* | *UL* | |
| Intercept | 2.13 | 0.04 | 2.05 | 2.21 | <.001 |
| NVO | -0.02 | 0.001 | -0.02 | -0.01 | <.001 |
| ND | -0.04 | 0.01 | -0.06 | -0.02 | <.001 |
| FB | 0.02 | 0.05 | -0.08 | 0.11 | .74 |
| IB | -0.03 | 0.04 | -0.11 | 0.05 | .41 |
| ND x FB | -0.01 | 0.01 | -0.03 | 0.02 | .54 |
| ND x IB | 0.005 | 0.01 | -0.02 | 0.03 | .66 |

*Note.* FB – Fake Block; IN – Invisible Block.

# Discussion

We investigated gaze allocation with respect to the agent in a novel experimental environment. Manipulating the type of uncertainty encountered in the environment, we induced various states of cognitive control. We differentiated between fixations based on whether they are initiated with the agent within high accuracy vision or outside of it. We found that between the two types of fixations there are differences in what is visually processed of the environment and incorporated in gaze allocation.

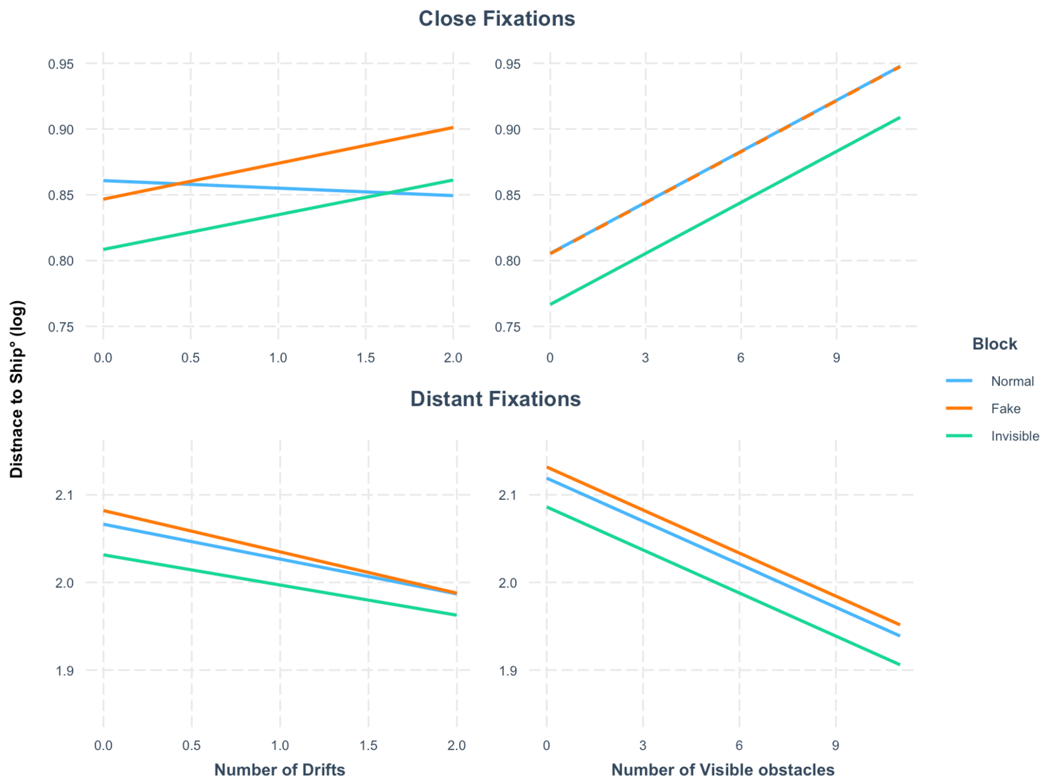


Figure 3: Effect on fixational distance to spaceship modulated by block type, NVO and ND in close fixations (top) and distant fixations (bottom).

There was a definite learning effect, as participants showed increased probability to successfully complete a trial with more trials played within a block. This was the case for the normal and invisible block, but not for the fake block (Figure 2). The lack of learning within the fake block could be explained by already high performance at the beginning of the block. Our analyses did not account for the learning itself, although we expect that the learning effect also affected the gaze allocation behaviour of participants.

Unsurprisingly, the characteristics of the visual environment played a significant role in shaping participants oculomotor behaviour, indicated by the main effect of NVO present in both close and distant fixations. However, the effect has opposite tendencies in the different types. When participants engage in close fixations, the distance to the agent increases with the number of visible obstacles. This is contradictory to our hypothesis, but it might relate to the need of monitoring the visual environment as it gets more complex while focusing on the agent. Confirmatory to our hypothesis however, when fixations are initiated further away from the agent, the distance decreases with increasing NVO. In fixations that were already close to the agent, there were no other effects besides NVO that affected their allocation. We argue that this might indicate bottom up, or stimulus-based visual attention control. At the higher cognitive level, the loss of control means that the uncertainty factor of drift cannot be processed. There are simply not enough cognitive resources left. This is why drift (the number of drift tiles or the block type) is not factored in gaze allocation. As a result, the fixational distance to the spaceship only depends on visible information (NVO). Incoming obstacles and subsequent changes within the environment shift the gaze away from the agent, resulting in larger distances. The limited resources are used on processing of visual information, rather than anticipating future situation or planning paths.

Although the main effect of NVO is also present in distant fixations, there is an additional main effect for the number of drift tiles. The effect might be ascribed to top-down, or goal-oriented control of visual attention, where participants actively plan for the potential effect of drift. This could mean that they feel enough in control on the cognitive level and thus have enough cognitive resources to anticipate the uncertain elements in the environment, in turn incorporating them in gaze allocation.

These results imply that different cognitive processes take place that consequently lead to fixations being executed either with the agent in central or in the peripheral vision. This means that simply the execution of a close or distant fixation might indicate a specific feeling of control (low and high respectively). Gaze allocation in general might therefore represent a highly sensitive intrinsic measurement for moment-to-moment changes in cognitive control induced by environmental uncertainty. However, in order to make a more confident statement about this, the roles of these fixations would have to be examined more closely.

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