Bees, Birds and Butterflies: Investigating the Influence of Distractors on Visual Attention Guidance Techniques

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(a) No distractors. (b) Static distractors. (c) Dynamic distractors.

Figure 1: We compared three Virtual Reality highlighting techniques (Deadeye, HiveFive and Circle) under different levels of visual distractors: (a) no distractors, (b) static distractors, and (c) dynamic distractors.

ABSTRACT

Visual attention guidance methods direct the viewer's gaze in immersive environments by visually highlighting elements of interest. The highlighting can be done, for instance, by adding a colored circle around elements, adding animated swarms (HiveFive), or removing objects from one eye in a stereoscopic display (Deadeye). We contribute a controlled user experiment (N=30) comparing these three techniques under the influence of visual distractors, such as bees flying by. Our results show that Circle and HiveFive performed best in terms of task performance and qualitative feedback, and were largely robust against different levels of distractions. Furthermore, we discovered a high mental demand for Deadeye.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

visual attention, attention guidance, virtual reality, perception

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1 INTRODUCTION

Visual attention and perception are widely studied in neurology and psychology [17, 21–24] but there is also growing interest in visualization and HCI to leverage findings from perception for design reasons [5, 14], for example to guide the user to interesting data patterns. While there exists much work on efficient attention guidance approaches for 2D displays (e.g., [33, 34]), there is considerably less work on guiding visual attention in realistic 3D environments, such as in augmented reality (AR) or virtual reality (VR) applications. Within these increased presentation spaces, viewers might feel overwhelmed or miss important patterns [10, 11]. To overcome this issue, previous work has suggested new attention guidance techniques tailored to immersive environments, such as adding animated swarms (HiveFive) [20] or removing objects from one eye in a stereoscopic display (Deadeye) [18, 19].

So far, these approaches were evaluated in terms of efficiency and accuracy in static surroundings [11, 12]. More realistic surroundings, however, might also consist of dynamic, distracting scenes. To evaluate how existing attention guidance techniques generalize to such settings, we present a user study on the influence of different levels of distractors. Our distractors consisted of additional non-moving and moving objects and we ordered them by using three levels of intensity to measure differences. We selected the techniques Deadeye [19], HiveFive [20], and circle-based highlighting [34], and gathered completion time, perceived workload, and subjective feedback. Our results could not show specific negative effects of distractors on individual techniques but suggest potential distracting influences of moving objects. In addition, Deadeye performed worst in terms of task completion and user experience.

2 RELATED WORK

Visual attention is an essential component of visual perception [4, 7], as it helps us prioritize important information over other stimuli we perceive [4, 7, 21, 24]. To guide the attention of the viewer to areas of interest, highlighting can be used. In the area of visualization, many approaches for highlighting data items in 2D displays have been studied [2, 14, 33]. Specifically, the notion of preattentive processing has attracted much work [2, 14, 33, 35]. Preattentive features, such as color or shape, can be detected within a single fixation of the eye before the first saccadic eye movement is triggered (< 200-250ms). In particular color, motion and stereoscopic depth have been found well suited to guide attention [34]. These are also the three conditions that we compare in our study.

Our main focus lies on highlighting techniques for VR/AR, and we are specifically interested in the role of distractors on these techniques. Compared to 2D highlighting, there is considerably less work on visual highlighting in VR/AR [16] and simply applying common 2D solutions (e.g., luminance adjustments of the target) might reduce the intended immersion or are perceived unnatural in such virtual environments [12, 20, 28].

To fill this gap, some first attention guidance techniques tried to direct attention with elements belonging to the scene such as an actor pointing towards relevant content to contribute to the intended immersion [11, 12]. Hu et al. [15] how gaze could be predicted in virtual environments. Other approaches investigated how motion can be used to guide in immersive environments. Lange et al. [20] present HiveFive that was inspired by swarms as they appear in several forms in real life and are adaptable to different surroundings. According to their results, HiveFive outperformed other visual attention guidance techniques (including Deadeye) in terms of accuracy, response time and perceived immersion. Building upon their work, we extend their investigations using a similar surrounding with additional non-moving and moving objects (distractions) and selected HiveFive as one of the highlighting techniques for our study.

Krekhov and Krüger [19] used modified stereo-vision to guide attention by only showing a target on one eye, but suppressing it completely on the other (called Deadeye). Within their work, they evaluated whether Deadeye can be perceived preattentively in general using a 3D TV and shutter glasses [19] as well as in virtual environments using a HMD [18]. Their results showed for both 2D circles and 3D cubes as targets that it is perceived preattentively regardless of distractors. Since this approach of highlighting is rather "minimally inversive" and does not interfere with the with the visual representation of a scene per se, we decided to include Deadeye [19] as another condition in our study. The third and last condition is simply adding a circular color highlight around the object of interest, resembling classical 2D approaches and serving as a baseline for our experiment.

In our work, we are specifically interested in the influence of distractions on these techniques. Only little work has focused on attention guidance techniques and distractors so far [25]. Some findings indicate that similar features of targets and distractors affect the perception of targets suggesting that similar features of attention guidance techniques and distractors (e.g., appearance or moving pattern) affect the intended guidance [26]. Since it is argued that especially motion directs the gaze [20, 33, 34], it is possible that moving distractors affect techniques that leverage motion (e.g., attractive flicker [33] or HiveFive [20]). However, we did not find related work regarding the influence of dynamic or moving distractors on attention or attention guidance techniques. Lange et al. [20] included some wind moving the leaves of the tree in their virtual environment but did not measure any implications. Pinto et al. [27] studied the effect of dynamic distractors on searching targets in a 2D setup using either moving or blinking.

Besides moving distractors, we also included some non-moving objects as another level of distractors, for which we found some previous research using common attention guidance techniques. McNamara et al. [25] studied the SGD ([2]) within a 2D environment using static distractors in two different user studies. While McNamara et al. [25] used extra modulations not highlighting any target region, we applied similar apple trees besides the target apple tree. Their results indicated a general higher search performance and distractors also outperformed compared to subtle or obvious modulations. McNamara et al. [25] argue that distractors could result in a more holistic gaze distribution over the image and refocusing avoids inattentional blindness. Therefore, it is possible that distractors motivate to look at the entire image and even though they only considered 2D images, their results may be similar for virtual environments.

3 METHODS

We aim to evaluate the influence of non-moving and moving distractors on attention guidance techniques. Our study extends the work of Lange et al. [20] by using a similar setup and surrounding but with an adjusted task with distractors.

Independent Variables. Our study involved two independent variables **visual attention guidance techniques** and **distractors**, each with three levels. Based on the rationale discussed in Section 2, we selected three different **visual attention guidance techniques** (see Figure 2): *Deadeye* [19] removing the target object from one eye, *HiveFive* [20] adding an animated flock of colored dots around the object, and the *Circle* baseline. We decided to use yellow as the highlighting color for the latter two, due to its good perception in peripheral regions and to conform with existing studies [20]. We opted to compare three **distractor levels** (see Figure 1) in our study. We shortly describe them here and point to the supplemental material for more details. *No Distractors:* The baseline condition did not have distracting objects. Hence, it only included the tree with the target object (an apple) [8], and the static background of the general virtual task environment [31]. *Static Distractors:* Extending the baseline, the static distractor level added a set of static, non-moving distractor objects. We chose distractors similar to our

(a) Deadeye. (b) HiveFive. (c) Circle.

Figure 2: Our selected techniques.

target object (i.e., further apple trees [8]) based on the findings of Olk et al. [26] as well as some further naturalistic objects (i.e., flower beds [30]). *Dynamic Distractors:* Further extending the static distractor level, we added different dynamic distractors for the third level of distraction. Comparable to our static scenario, we added moving distractors similar to one of our attention guidance techniques by adding two swarms using the flocking algorithm by Reynolds [29]. Like Lange et al. [20], we also included some wind as well as further animals and moving nature phenomena.

Tasks. Our participants had to fulfill a mandatory training task in a neutral starting environment to practice clicking with the VR controllers in order to avoid hardware struggles. Our study task was inspired by Lange et al. [20], as for each condition, participants had to find and click on ten randomly-chosen, highlighted apples. In case participants clicked on the wrong apple on the target tree, the target apple remained highlighted.

Dependent Variables. Task performance was measured through completion time by considering the time in seconds elaborating between the appearance of the highlighting and the selection of the correct target. We also measured errors but due to the page limit, it is described and evaluated in the supplemental material. User experience was measured after each distractor level through NASA TLX [13] and a set of custom questions similar to the previous studies of Lange et al. [20] and Krekhov and Krüger [19] (see supplemental material). In the concluding questionnaire, the participants had to rank the techniques and give feedback on their overall experience. We tested our study design in a pilot study with 5 participants (2 females and 3 males) and changed some minor configurations that are described in more detail in the supplemental material.

Study Design. We designed a within-subject study to evaluate the task performance and user experience of the independent variables **Technique** (Deadeye vs. HiveFive vs. Circle) and **Distractor Level** (No Distractors vs. Static Distractors vs. Dynamic Distractors). Thus, participants had to perform 9 conditions (3 techniques x 3 distractor levels). Each condition consisted of 10 trials with randomly selected targets, resulting in 30 trials per **Technique** or **Distractor Level** and overall 90 per participant. We counterbalanced the techniques using a Latin square design and the order of the presented distractor level of each technique was randomized for every participant.

Hypotheses. According to our research questions, we decided for the following hypotheses:

- H1: *The completion time increases for all techniques with increasing distractor level.* Since more entities increase the information that our brain perceives, we assume that participants take longer to find a highlighted target.
- H2: *The completion time increases more for HiveFive with dynamic distractors than with other techniques.* As HiveFive has some similar properties (color, motion) as some of our dynamic distractors, we suspect that they have the most negative impact for this technique [26].
- H3: *Deadeye has higher mental demand and effort compared to other techniques with increasing distractor level.* Due to its subtle property, we suggest that strong distractors guide itself and hence, increase the subjective workload to find the highlighted target [26, 34].

Apparatus. The study was conducted within the VR Laboratory of our institute. We used an online survey tool **Limesurvey** [1] to create and conduct our questionnaires. We presented them on a PC and a standard 2D display using Windows 10. Since the main part of our user study was within VR, we used the Windows Mixed Reality Headset HP Reverb G1 and their associated motion controllers. We implemented the entire virtual study environment with the game engine **Unity**[2] using Version 2021.2.8f1 and the **Mixed Reality Toolkit**[3] (MRTK) for immersive MR Headsets with the Version 2.7.3.0. Both versions were the latest version at the start of our implementation.

Procedure. The study was performed under current COVID-19 hygiene measures. After completing a consent form and a demographic questionnaire including vision ability tests, we let participants familiarize themselves with the virtual environment by starting with the training task. Then, the study task was performed in each condition. For filling out the questionnaires, participants took off the HMD. The study concluded with a final questionnaire and the participants were compensated with 10 Euro for an approximately 45-60 minutes study duration.

[1] Limesurvey Homepage: https://www.limesurvey.org/
[2] Unity Homepage:https://unity.com/
[3] MRTK Documentation:https://docs.microsoft.com/de-de/windows/mixed-reality/mrtk-unity/mrtk2/?view=mrtkunity-2022-05

Distractor Level	Deadeye	HiveFive	Circle
No	M=9.94 (SD=18.77)	M=2.01 (SD=6.95)	M=1.77 (SD=6.90)
Static	M=22.15 (SD=43.04)	M=2.09 (SD=6.99)	M=1.67 (SD=6.86)
Dynamic	M=17.17 (SD=19.92)	M=2.77 (SD=6.69)	M=2.22 (SD=6.64)

Table 1: Mean and SD of CT in seconds.

	F-value	p-value	η_p^2
Technique	(1.002, 29.07)=16.65	<.001	0.365
Distractor Level	(2, 58)=1.295	.282	-
Technique:Distractor Level	(4, 116)=1.232	.301	-

Table 2: ANOVA results of CT.

	Mental Demand			Effort		
Distractor Level	Deadeye	HiveFive	Circle	Deadeye	HiveFive	Circle
No	M=7.43 (SD=3.84)	M=1.77 (SD=1.86)	M=1.60 (SD=1.91)	M=7.60 (SD=3.73)	M=3.00 (SD=1.78)	M=2.40 (SD=2.36)
Static	M=8.00 (SD=4.63)	M=1.87 (SD=2.03)	M=1.87 (SD=1.89)	M=7.70 (SD=4.24)	M=2.57 (SD=1.93)	M=2.43 (SD=2.21)
Dynamic	M=11.27 (SD=4.63)	M=4.13 (SD=1.88)	M=2.80 (SD=1.95)	M=10.70 (SD=4.13)	M=4.67 (SD=1.69)	M=3.67 (SD=2.24)

Table 3: Mean and SD of MD and E.

4 RESULTS

We recruited 30 participants via university mailing lists and social media (9 female, 21 male), of different age groups between 18 and 55 years (mode= *22 to 25*). 29 participants had correct or corrected-to-normal vision, only one mentioned that they had a red-green weakness. We had 10 participants with a dominant left eye and 20 with a dominant right eye. Most participants had only little VR experience (20/30 between 0 to 1 on 5-point Likert Scale), while some had high VR experience (10/30 between 2 to 4). Before our multivariate analyses, we checked our resulting data regarding normal distribution by applying Shapiro-Wilk-Test, revealing no normal distributions in most cases. However, simulations studies showed that the ANOVA is very robust against Type I error [3, 32]. Therefore, we decided to continue with computing repeated measures ANOVAs with a 2 x 3 design on a significance level of α=.05 and Bonferroni-adjusted post-hoc tests to examine our proposed hypotheses. In case of lacking sphericity, we applied the Greenhouse-Geisser or Huynh-Feldt adjustment as recommended by Girden [9]. Further, we used graphical analyses to identify potential outliers. For details on normality and outliers we refer to the supplemental material.

4.1 Task Performance

In the following, we report the results of the completion time (CT). We received 90 values per participant (9 conditions x 10 trials) which we aggregated by averaging over the trials per participant and then over the participants' means to gather the overall mean (M) and standard deviation (SD) per condition. Table 1 provides exact descriptive statistics and Figure 3 (completion time) shows the visual representation with confidence intervals. Since CT cannot be negative we clipped the confidence intervals to zero. In case of CT, we decided to include outlier values, as they resulted not from errors but real measurements [1] and excluding the detected outlier case from ANOVA does not lead to significant changes. The ANOVA is reported in Table 2.

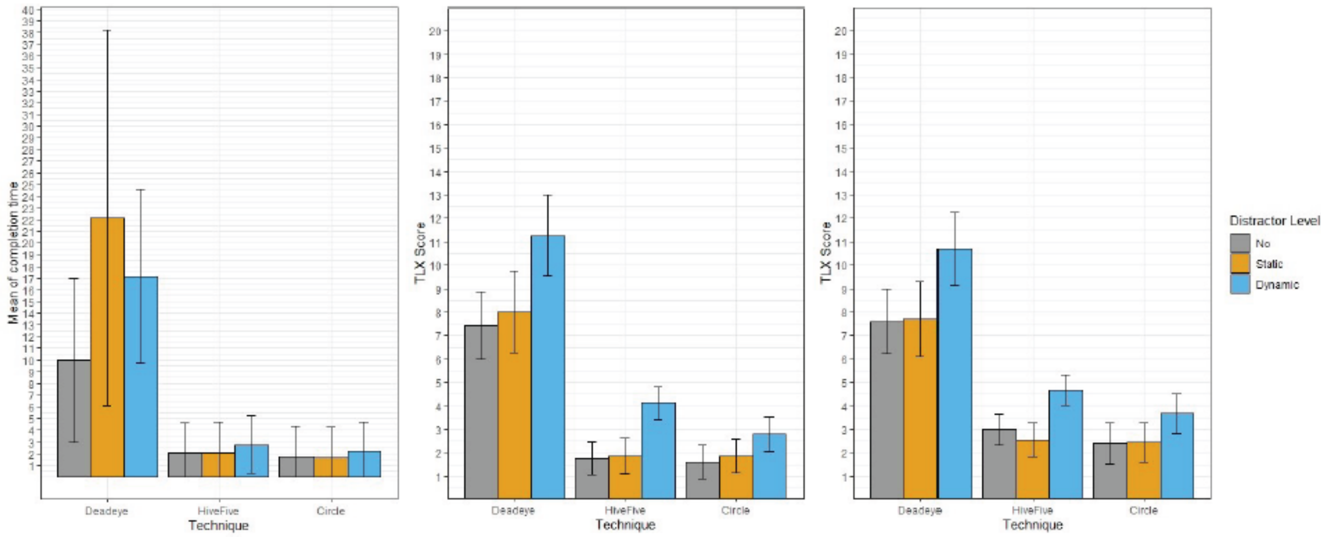
Deadeye has the highest completion time for all distractor levels. HiveFive and Circle performed similarly and were substantially faster than Deadeye in all conditions (see Figure 3a). For HiveFive, the mean completion time was slightly higher for dynamic distractors compared to no distractors. However, this is not the case for Deadeye and Circle. While Deadeye has the highest completion time for static distractors, static distractors have the lowest mean for Circle (see Table 1). Our ANOVA revealed a significant main effect between our three techniques on completion time (see Table 2) but neither for distractors nor for a significant interaction effect. According to Cohen [6], our effect size of $\eta_p^2 = 0.365$ of our only main effect can be interpreted as a large effect. Post-hoc tests revealed significantly higher mean scores for Deadeye (M=16.42, SD=3.55) compared to HiveFive (M_{Diff}=14.13, 95%-CI [5.194, 23.059], p<.01) and Circle (M_{Diff}=14.53, 95%-CI [5.618, 23.435], p<.001).

We cannot confirm H1: The completion time increases for all techniques with increasing distractor level. For H1, we wanted to compare our distractor levels pairwise for each technique. However, we did not find a significant effect for the distractor level as well as for the interaction effect. Therefore, we cannot confirm H1. Nevertheless, based on Figure 3a, all techniques have higher means of completion time for dynamic distractors compared to no distractors. Hence, we assume that our dynamic distractors affected the perception of highlighting in some way.

We cannot confirm H2: The completion time increases more for HiveFive with dynamic distractors than with other techniques. For H2, we compared the completion time of all techniques within the dynamic distractor level. Due to a lacking significant interaction effect, we cannot confirm H2. While we cannot prove a quantitative effect of distractors on HiveFive, participants mentioned being disturbed by distractors (18 statements, see comment analysis in the supplemental material). However, Figure 3a shows increasing differences for Deadeye for the dynamic distractors. This might have other causes, such as the novelty of the technique as stated by P14: *""Deadeye" was the most difficult [...] because personally I am not too familiar with techniques like this."*

4.2 User Experience

In the following, we report the results of the NASA TLX subscales mental demand and effort which were relevant for H3. The evaluation of the other subscales as well as the custom questions, and a comment analysis are in the supplemental material. We averaged each of the 9 values per participant of each subscale to gather the



(a) CT (negative clipped to zero, in sec.). **(b) MD (0: very low, 20: very high).** **(c) E (0: very low, 20: very high).**

Figure 3: Error bars showing the 95% confidence interval for completion time (CT), mental demand (MD) and effort (E).

overall mean and SD per condition (see Table 3). A visual representation of the results can be seen in Figure 3 (mental demand) and Figure 3 (effort). The ANOVA results for each subscale are shown in Table 4. By excluding one outlier and re-applying ANOVA, we found a significant interaction effect of our independent variables (Greenhouse-Geisser $F(1.95, 52.62)$=3.461, p=.40) showing that MD increases significantly for Deadeye with dynamic distractors. However, subsequent studies are needed for confirmation. For effort, excluding the detected outliers did not lead to different results.

Deadeye has the highest mental demand and effort. HiveFive ranks second and Circle has the lowest mental demand and effort (see Table 3 and Figure 3). Based on the results of our ANOVA, we applied post hoc tests for both of our subscales. For mental demand, all three techniques differ significantly from each other. Deadeye (M=9.21, SD=4.43) and HiveFive (M=2.67, SD=2.41) resulted in (M_{Diff}=6.54, 95%-CI (4.562, 8.519), p<.001). Deadeye and Circle (M=2.16, SD=2.35) yielded in (M_{Diff}=7.05, 95%-CI (4.917, 9.175), p<.001). For effort, post-hoc tests showed that Deadeye (M=8.95, SD=5.09) has the highest mean score and significantly differs from HiveFive (M_{Diff}=5.43, 95%-CI (3.737, 7.113), p<.001) and Circle (M=2.93, SD=3.07) (M_{Diff}=6.02, 95%-CI (4.064, 7.982), p<.001). While HiveFive and Circle significantly differed for mental demand (M_{Diff}=0.51, 95% CI (0.043, 0.968), p=.029), there was none for effort (M_{Diff}=0.59, 95%-CI (-0.148, 1.343), p=.152).

Dynamic distractors caused the highest mental demand and effort. The pairwise comparison of distractor level for mental demand showed significantly higher mean scores between dynamic distractors (M=6.26, SD=2.9) and both other distractor levels (No: M_{Diff}=2.54, 95% CI (1.729, 3.351), p<.001; Static: M_{Diff}=2.22, 95% CI (1.146, 3.291), p<.001). However, there is no significant difference between no and static distractors (M_{Diff}=0.32, 95%-CI (-0.397, 1.041), p=.79). For effort, a similar pattern could be seen. Dynamic distractors (M=6.55, SD=3.51) significantly differed from both other distractors (No: M_{Diff}=2.07, 95%-CI (1.114, 3.024), p<.001; Static: M_{Diff}=2.17, 95%-CI (1.049, 3.295), p<.001), but there is no significant difference between no and static distractors (M_{Diff}=1.03, 95%-CI (-0.776, 0.983), p=.99). Hence, we assume that dynamic distractors affected the user experience to some degree.

We cannot confirm H3: Deadeye has higher mental demand and effort compared to other techniques with increasing distractor level. Although we found significant main effects for mental demand and effort for both of our independent variables, we did not find a significant interaction effect. Hence, we cannot confirm our H3. However, since both subscales were significantly higher for Deadeye compared to the other techniques, Deadeye might be more exhausting. To confirm this, more in-depth studies are necessary.

5 POTENTIAL RESEARCH DIRECTIONS AND LIMITATIONS

As with all empirical work, there are several factors that potentially limit the findings of our study. For one, our sample size was small. Further, participants missed the feedback of successful interactions, which might influenced our results. In addition, the color choice of HiveFive and Circle could be another potential limitation. We propose to test immersive highlighting techniques with diverse colors, as color strongly guides on its own [34]. Naturally, there are also possible interaction effects of a highlighting color with the background colors.

Does Deadeye require training and what effects would its long-term usage have? Our results showed that Deadeye had higher values regarding both, the completion times and the subjective task load. Some participants considered the technique to be irritating or causing discomfort since, for example, expressed by P3 (*"Uncomfortable for the eyes."*) Other participants noticed a learning effect (*"[T]here*

	Mental Demand			Effort		
	F-value	p-value	η_p^2	F-value	p-value	η_p^2
Technique	(1.068, 29.91)=69.40	<.001	0.713	(1.213, 33.974)=59.14	<.001	0.679
Distractor Level	(1.688, 47.28)=32.01	.001	0.533	(2, 56)=19.82	<.001	0.414
Technique:Distractor Level	(1.935, 54.18)=3.191	.051	-	(2.43, 68.08)=1.75	.18	-

Table 4: ANOVA results of MD and E.

is a learning progress before [Deadeye] performs as the others” (P11)) which we saw in our data as well. In general, the completion time mean decreases for consecutive runs for all techniques. However, the mean of Deadeye decreases more drastically after the first run, for a detailed analysis we refer to the supplemental material. To the best of our knowledge, there exist no studies on the longitudinal effects of Deadeye. Thus, it would be interesting to investigate this method in a longitudinal study to also study potential drawbacks like exhaustion.

In which scenarios is motion more distracting than guiding? Waldner et al. [33] report a trade-off between effectiveness and annoyance for motion. Although we could not confirm *H2*, we saw some evidence for this within the comments for HiveFive. For example, expressed by P3 *“The movement was slightly annoying”*. While some perceived the swarm-based motion intrusive, others stated that the animation supported the target perception as P1 argued that *“[HiveFive is][e]ye catching through movement”*. Some participants also commented that distractors made it difficult, in particular bees (*“The yellow bees have a high resemblance to the yellow highlighting particles.”(P6)*). As HiveFive is similar to a bee swarm by design, this is consistent with previous findings, stating that target and distractors are more likely confused if they share common characteristics [26]. Thus, we suspect that motion-based guidance in busy scenarios with conflicting cues might be less effective. However, more research is required to confirm this.

Where is the sweet spot between attracting attention and preserving immersion? Related to the trade-off mentioned above, it requires more research to which degree an attention guidance technique could and should disturb immersion in order to be noticed. Our technique selection attempted to cover such a spectrum by including rather subtle (Deadeye) to immersive and noticeable (HiveFive) to static recognition without immersion (Circle) which our results reflect. Hence, one has to find the sweet spot of guiding attention while not disturbing immersion and adjust depending on the use case. According to P19, this worked for HiveFive: *“It is a good compromise between recognizability and immersion”*.

6 CONCLUSION

We studied the influence of distractors on attention guidance techniques in immersive environments under the impact of non-moving and moving objects distractors. While we could not confirm our hypotheses regarding specific influences of distractors on certain techniques, we could see a general negative effect of dynamic distractors. Further, Deadeye seemed to have the weakest task performance and user experience. Our work could be a starting point for more in-depth studies to build up a taxonomy containing usage scenarios and suitable attention guidance techniques for selection tasks with distractors.

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