Performance as Agency? Investigating the Trade-off between Sense of Agency and Performance in Target Selection with Preemptive Assistance in VR

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***Abstract*—Virtual Reality systems enable immersive experiences by providing users with rich interaction techniques in tasks such as target selection and object manipulation. With the increased integration of intelligent assistants, these interaction techniques continue to improve users' performance by anticipating their goals and preempting their actions. It is yet unclear, however, if such advanced interaction techniques negatively influence users' sense of agency. We explore this trade-off through a user study (N=12) on target selection tasks while varying the levels of preemptive assistance and task difficulty. We measured the sense of agency with both interval estimation based on the intentional binding paradigm and participants' self-reports, which is compared with quantitative performance and behavior metrics. Our results reveal that while a higher level of assistance improved performance, the sense of agency remained stable in difficult task settings and increased in easy task settings with more assistance, which might be due to participants becoming more proactive and attentive under high-assistance conditions. We provide guidelines for future intelligent interaction techniques that aim to balance performance with the sense of agency.**

***Index Terms*—Virtual reality, Agency, Human-computer interaction, Interaction techniques**

I. Introduction

Virtual Reality (VR) offers opportunities for users to engage in virtual environments beyond the constraints of the physical world. It open up new dimensions of interaction, enabling users to explore and manipulate 3D virtual spaces with a freedom that traditional 2D interfaces cannot match. The high level of immersiveness and interactivity in VR makes it a promising platform, unlocking exciting possibilities for applications such as gaming, training, and productivity [1].

Being able to effectively interact with the virtual space is crucial for the immersive and present user experience. Over the years, research has designed numerous techniques that scaffold different categories of interaction (e.g., target selection, object rotation and translation). Most of these interaction techniques are grounded in the *direct manipulation* paradigm, aiming to grant users full autonomy over their actions to navigate and manipulate virtual elements. While a high degree of control generally enhances the sense of presence, these techniques are oftentimes found cumbersome to maneuver in extreme scenarios, such as selecting distant or densely packed objects or performing intricate rotations, consequently resulting in fatigue and reduced sense of presence.

In recent years, research has increasingly explored the alternative paradigm: rather than requiring users to perform all interaction tasks manually, can intelligent assistance automate or delegate parts of the process? Powered by advanced machine-learning (ML) algorithms, this body of research investigated the feasibility of predicting users' intentions [2] as well as preemptive executing inferred tasks before users take action [3], [4]. These methods have shown improvements over traditional interaction techniques in task performance across diverse scenarios and task settings, signaling a promising future where users can bypass cumbersome interactions through support from intelligent agents.

Despite the optimism surrounding these advancements, a critical question remains: how do these advanced interaction techniques impact the user's sense of agency (SoA)? SoA describes the subjective experience of having control over one's actions and their outcomes, which is essential to immersive and present experiences within a virtual environment [5]. As these intelligent systems proactively take on more decision-making and task execution, users may feel less in control over their interaction with the virtual environment. Yet, most current research merely emphasizes optimizing and validating performance metrics, overlooking this subjective but crucial dimension of user experience.

To address this gap, our paper explores how varying levels of assistance that preempt users' actions affect SoA in target selection tasks in VR. We conducted a between-subject user study with 12 participants who completed a target selection task in a controlled virtual environment. The experiment manipulated two variables: ASSISTANCE (3 levels), which enabled preemptive selection triggering at different distance thresholds beyond targets' physical boundaries, and task DIFFICULTY (2 levels), represented by objects of varying sizes and densities reflecting diverse scenarios. To measure SoA, we recorded both participants' self-reports on the Agency Questionnaire [6] and an implicit measure of interval estimation within the intentional binding paradigm [7]. To investigate potential trade-offs brought by assistance we also measured participants' task performance using metrics of task completion time and error count and compared them with the agency data. We also assessed user behavior during target selection such as movement distance and speed to further interpret the results.

We investigated the following research questions:

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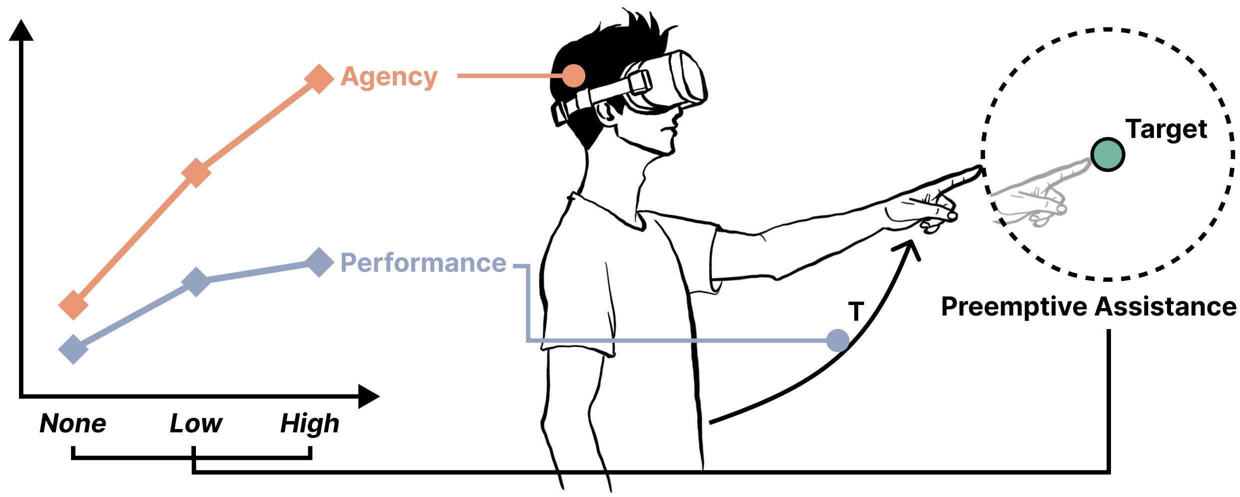


Fig. 1. Our 12-participant user study empirically investigated the relationship between the sense of agency and task performance in a target selection task in VR under varied levels of assistance that preempted the action. While the sense of agency, measured using the intention binding paradigm, remained stable across different levels of assistance in more difficult task configurations, it increased alongside performance as assistance levels increased in easy task configurations, which contradicts the traditional perspective on the trade-off. We provide further discussions on this result and contribute a design guideline for future intelligent target-selection techniques that aim to balance users' performance and agency.

RQ1: How do different levels of preemptive assistance affect participants' SoA in target selection tasks in relationship to their performance?

RQ2: If any, what specific factors within the task selection process contribute to variations in perceived agency?

Our results show that participants' SoA varied differently from their performance as the magnitude of preemptive assistance increased. The specific variations depended on the task difficulty: While higher levels of assistance led to improved performance, SoA measured by interval estimation error remained stable in difficult task settings, and interestingly, increased in easy task settings. Our correlation analysis showed that this is likely due to the changes in user behavior in target selection - with higher levels of assistance, users became more proactive in their sensory feedback loop in anticipating the outcomes as reflected in their hand movement behavior.

Our work contributes the following:

- An empirical study that quantitatively investigated the effect of varying levels of preemptive assistance on users' SoA, extending beyond traditional performance metrics in VR target selection tasks.
- Guidelines/insights for designing future target selection interaction techniques that integrate intelligent assistance that preempt users' actions and aim to balance both performance and SoA.

II. Bcakground and Related Work

Our work builds on prior research on SoA, intentional binding paradigm, agency in human-computer interaction (HCI), and target selection in VR.

A. Sense of Agency

SoA describes the feeling of internally being able to control one's own actions to influence events in the external environment [5]. Individuals with a strong SoA would recognize themselves as the initiators of voluntary movements rather than external agents [8], [9]. Studies show that this feeling of being "in control" is tied closely to one's self-consciousness and identity formation [10], and the effectiveness of interactions and decision-making at interpersonal and societal levels [5].

Research in cognitive neuropsychology has extensively studied this critical concept to understand its underlying cause and mechanism. Over the years, two main models have been proposed [11]: On the one hand, the *Predictive Model* suggests that SoA arises when the predicted outcomes of one's actions and the actual sensory feedback received match each other [12]. This model relies on internal forward models that anticipate the sensory consequences of motor commands. A strong SoA is experienced when these predictions align with reality. Supporting evidence for this model includes work by Libet et al. which demonstrated that the brain generates readiness potentials before we are consciously aware of our intentions to act [13]. Conversely, the *Postdictive Model* argues that SoA is retrospectively constructed based on the outcomes of actions and their contexts [14]. This model asserts that agency results from both sensory-motor processes as well as higher cognitive functions such as attention, reasoning, and memory [15]. Based on this perspective, the brain reconstructs a sense of control over an action by evaluating whether the outcome was expected or desirable, along with other contextual cues. A notable hypothesis within this model is the mental causation theory by Wegner et al. [16], which suggests that free will is perceived when a thought precedes, aligns with, and appears to solely and apparently cause an action.

These opposite views show the complex nature of SoA and the necessity of taking multifaceted approaches to research and measurement. Prior studies have adopted methods such as medical imaging [17], electrophysiological recordings [18], and specially designed behavioral assessments [19] to measure SoA experienced by the subjects. These techniques often require specialized equipment and are typically limited to controlled lab settings. To achieve greater practicality and flexibility, researchers have also relied on subjects' self-reports [6], [20], which usually involve rating responses to one or a few specific prompts, and on the intentional binding paradigm, which implicitly assesses agency through the temporal binding effect (see Section II-B for a detailed discussion). Notably, these two methods correspond to the two aforementioned models of the origin of agency respectively: self-reports reflect retrospective introspection (postdictive), while the intentional binding paradigm captures sensory and internal model discrepancies (predictive). This study applies both methods for the comprehensiveness of SoA measurement and analysis.

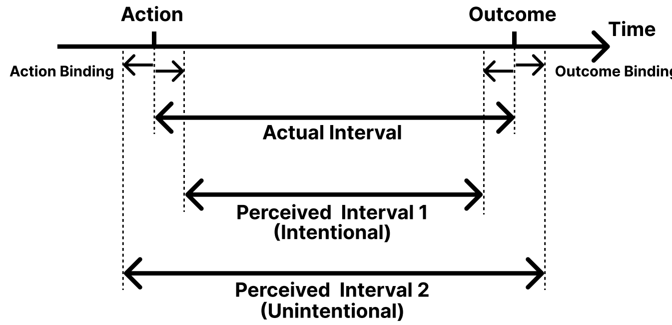


Fig. 2. Illustration of the intentional binding phenomenon.

B. Intentional Binding Paradigm

The intentional binding paradigm is illustrated in Figure 2. It was first observed by Haggard et al., who found that the perceived timing of a voluntary action and its sensory outcome tends to converge in a person's perception, resulting in a seemingly shortened interval between them [21]. The shortened perceived interval is due to two components: action binding, where an action is perceived as occurring later than it actually does, and outcome binding, where the outcome is perceived as happening earlier. The combined of these shifts forms the total binding effect, with a greater total indicating a stronger SoA. Conversely, if the action is unintentional, it's perceived as happening earlier and the outcome as later, leading to a negative total binding and a lower SoA.

To measure both action binding and outcome binding, researchers typically use the Libet Clock method [22], adapted by Haggard, which involves asking participants to observe a running clock and report the perceived timing in repeated measurements. Nevertheless, this method requires considerable eye attention and proves impractical in tasks rich in visual stimuli such as target selection. An auditory variant of the Libet Clock introduced by Martinez et al. [23] was tested in our pilot study, but participants faced difficulties in accurately recognizing timed auditory cues at the preset rate.

We consequently adopted the interval estimation method proposed by Ebert et al. [7]. The interval estimation method requires participants to estimate the perceived time between an action and its outcome in each trial. Each trial varies the interval randomly (see Section III-B for details), and after each one, participants report their time estimate. These estimates are then compared to the actual intervals to calculate the estimation errors, i. e., total binding. Although this method is considered less reliable than the Libet clock method and cannot specify whether the error is due to action or outcome binding, it is more practical in target selection tasks. To minimize errors, we averaged the results over a substantial number (30) of trials for each participant.

C. Agency in HCI

Agency in human-computer interaction emphasizes the importance of user feeling in control of actions and interaction with digital media and the physical world. Computer interfaces that enable this can lead to pleasant and meaningful user experiences; otherwise, users may feel constrained or disengaged [24]. Past work has investigated how agency varies with different computer interfaces. For example, Coyle et al. examined SoA comparing Skinput [25], a novel input device that attaches a piezoelectric microphone to the user's forearm, with traditional physical interactions like pressing a button [26]. Similarly, Martinez et al. explored the effects of touchless gesture-based interactions on SoA [27], unveiling that touchless interactions could achieve a similar level of agency as physical touch-based methods.

A key paradigm rooted in user agency is *direct manipulation*. First introduced by Ben Shneiderman in 1983, *direct manipulation* emphasizes providing users with an immediate, intuitive way to interact with digital objects by offering continuous feedback and reversible actions [28]. This approach reinforces users' SoA by allowing them to observe the direct consequences of their actions, fostering confidence and engagement with the system. However, human capabilities have inherent boundaries. *Direct manipulation* requires cognitive resources and physical effort from users [29], which oftentimes fall short [29] when tasks or interactions become overly complex or demanding (e.g., managing overmuch virtual contents [30]). Overwhelming users with excessive options for control in such cases could result in decision fatigue, which ultimately reduces SoA [31].

Alternatively, the *software agent* paradigm proposes the use of autonomous agents to support users in handling tasks, making appropriate decisions, and executing actions on their behalf [32]. Over the years people have instantiated the *software agent* paradigm in various forms, ranging from email filtering agents (e.g., MailRank [33]) and voice assistants (e.g., IBM Watson [34]), demonstrating practical value in alleviating users' task load. With recent advancements in artificial intelligence and machine learning, the capabilities of *software agents* have grown significantly, enabling more sophisticated support for users in a wider range of tasks. However, the increased autonomy from *software agents* diminishes users' SoA. With too much delegation by the agents, users may feel detached from the decision-making process, leading to potential disengagement and diminished ownership over tasks.

Designing for agency in human-computer interaction therefore requires a nuanced understanding of the balance between enabling user control and providing assistance. Several studies have exploratorily investigated SoA under hybrid approaches that combine elements of direct manipulation with agent-based support. For example, Kasahara et al. investigated the trend of user agency in a simple tapping task enhanced with electrical muscle stimulation that preempted user actions at various timings [20]. They reported that participants experienced a reduction in their SoA as the preemptive gains increased; the resulting SoA curve could be approximately modeled by a softmax function. More recently, Didion et al. examined the context of image generation [35]. They found that participants' SoA diminished as the realism of the generated images decreased, such as when the image content became more abstract. Our work contributes to this limited body of literature on understanding the relationship between SoA and assistance in target selection in VR.

D. Target Selection in VR

Target selection is one of the most fundamental interaction types in virtual reality [1], allowing users to access and engage with elements or digital content in virtual environments. Efficient interaction techniques for target selection are crucial for seamless and immersive user experiences in VR. In this regard, past work has proposed various techniques, such as ray-casts [36] and go-go [37] and Tiny hands [38], each offering unique functionality and design rationale. However, the majority of these techniques only demonstrate limited practicality; while effective in some scenarios, their efficiency often declines in others, especially in edge cases involving small or distant targets or where targets are occluded or cluttered by other virtual elements. Prior research has continuously focused on refining and enhancing these techniques by integrating additional mechanisms. For example, Lu et al. investigated the bubble mechanism for ray-casting in VR, which simplifies target acquisition by identifying the nearest target to the ray [39]. Nonetheless, most of these refinements add complexity to interactions, making the control process unintuitive. Oftentimes, they also induce additional challenges; for example, the Bubble Ray technique underperforms in the presence of nearest neighbor distractors [4].

In recent years, substantial research has explored an alternative paradigm: instead of requiring users to fully control the selection process, can we automate and delegate parts of this process by incorporating machine learning algorithms to facilitate target selection? These advancements introduce methods that predict the user's intended target and integrate these predictions into the interface [40], [4], [3], [41]. For example, Yu et al. [3] proposed a computational framework that determines the optimal timing for presenting intelligent suggestions on target selection that balances accuracy and user effort. Moon et al. [4] applied biomechanical simulations to train a target selection agent with a real-time perception-action loop. Their study showed that integrating the agent's target inference with the ray-cast technique significantly reduces target selection time and error. While these methods introduce software agents into target selection, a task traditionally relying on direct manipulation, they primarily focus on optimizing performance without considering how these processes affect the user's SoA. Our work seeks to address this gap by investigating how varying levels of assistance that preempt users' actions impact the experienced SoA.

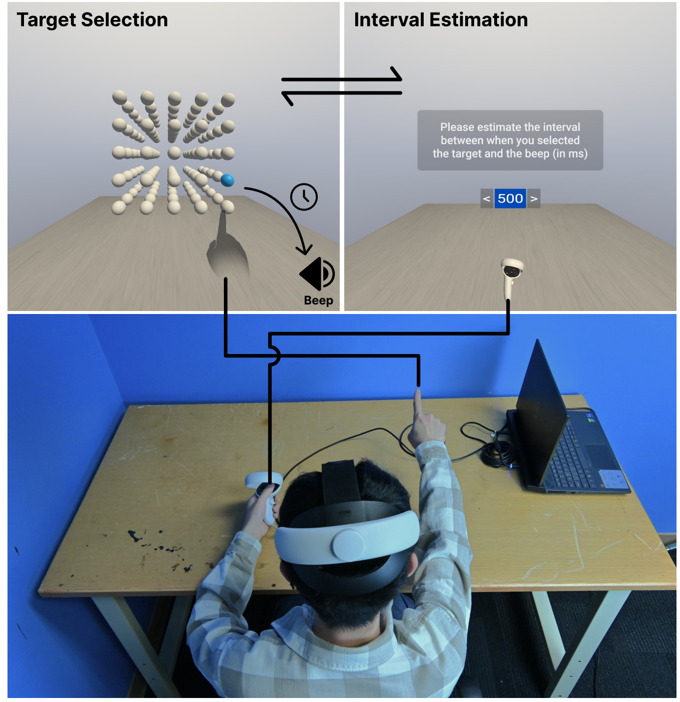


Fig. 3. Experiment procedure and setup. Participants were equipped with a Meta Quest 2 headset. In each trial, they first performed a target selection task by pointing at a target sphere with the index finger of their dominant hand. This generated a beep sound after a short interval. They were then instructed to give an estimation of the perceived interval.

III. Experiment

We designed a within-subject experiment involving 12 participants who performed a target selection task. To prototype experiences of intelligent suggestions preempting users' actions across different task scenarios, we designed conditions that varied in levels of ASSISTANCE (*None*, *Low*, *High*) and task DIFFICULTY (*Easy*, *Hard*).

A. Target Selection Task

We instantiated a simple target selection task (see Figure 3), inspired by prior work [39]. In each trial, participants were presented with a $5 \times 5 \times 5$ uniform grid of spheres positioned in their field of view. The radius (r) and margin of adjacent spheres (d) in each condition were determined by the DIFFICULTY level (Section III-A1). A calibration procedure was conducted at the start of each condition to ensure that the center of the spheres was positioned at 0.8 times the length of one arm away from the arm joint. The center of the spheres was also aligned with the participants' eyes along the x and y axes. This configuration replicates common potential challenges in 3D target selection, including occlusion and density. We removed spheres located on the third row and third column (except the nearest one) for their full invisibility.

Before each trial, participants prepared by placing their dominant hand inside a "reset" cube ($0.2\,m \times 0.05\,m \times 0.2\,m$). Upon readiness, one of the spheres would be highlighted in dark blue to indicate the *target* whereas others (referred to as *non-target*) would remain the same. Participants were free to start the trail by leaving the "reset" cube at their will and were instructed to hit the target sphere with the index fingertip of their dominant hand as quickly and accurately as possible. This index-pointing method was chosen as it embodies a basic isomorphic VR interaction technique; it is simple and also considered one of the earliest referential gestures humans adopt in childhood [42].

Upon hitting the *target*, it would change color to light blue. Participants were required to dwell their finger on the *target* to confirm the selection as intentional. On the contrary, hitting a *non-target* sphere would also turn it light blue, but dwelling on it would turn it red to indicate an incorrect selection. A beep sound would signal a successful selection after a brief time delay, further explained in Section III-B.

1) DIFFICULTY*:* The necessity and extent to which assistance should be applied depend on the magnitude of challenges users encounter when performing the tasks. To understand how the effect of preemptive assistance on SoA would vary across different task settings, we designed our experiment with two levels of DIFFICULTY configurations:

- **Easy** ($r = 5\ cm$, $d = 10\ cm$)**:** Spheres with a large radius and wide margins in the condition would lead to reduced the index of difficulty (ID) and the movement time (MT) inferred from the Fitts' Law [43], [44]. The large margin leads to a sparse distribution of spheres which increases the ease of selecting the correct sphere without mistakenly engaging adjacent ones.
- **Hard** ($r = 1\ cm$, $d = 3\ cm$)**:** This setup simulates scenarios that require participants to select between closely packed, small objects. The smaller radius would increase ID and MT. The reduced margin increases the density, leading to a higher tendency of accidentally mis-selecting neighboring *non-target* spheres.

The study purposefully equalized the distance between the center of spheres and the "reset" cube in both configurations through calibration, so that the average distance of hand movement remained constant and did not contribute to varied ID or MT according to Fitt's Law.

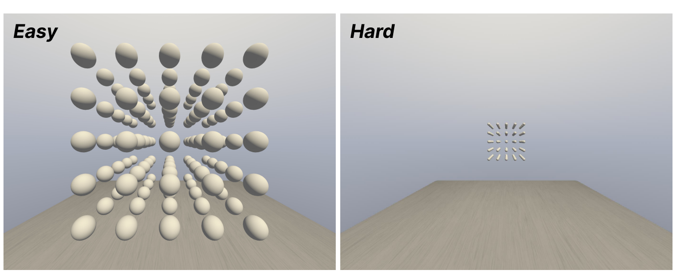


Fig. 4. Target selection task settings of two difficulty levels.

2) ASSISTANCE*:* Our assistance design was intended to reflect various levels of integration of intelligent selection which preempts users' actions. Independent of the specific interaction methods and metaphor, the assistance should aim to address the intrinsic difficulty posed by the target selection tasks. Inspired by prior studies on target expansion [45], [46] and preemptive action [20], we designed an assistance mechanism that allowed participants to select the *target* with a distance threshold beyond its physical boundary by the preemptive gain k. Formally, the state S_t (1 - hit, 0 - unhit) of the *target* with radius r and given the surface distance D between the *target* and the fingertip can be defined:

$$S_t = \begin{cases} 1, & \text{if } D \leq r \cdot k, \\ 0, & \text{if } D > r \cdot k. \end{cases} \tag{1}$$

Notably, this mechanism only enables positive assistance experiences, where the preemption is always applied to the *target* sphere in each trial. If the boundary of assistance crosses other non-target spheres, the assistance will prioritize selecting the target sphere if the fingertip is in the intersection. Compared to target expansion, our assistance mechanism does not provide the visual stimuli of target size changes. We aimed to gain a more generalizable understanding of this implicit preemptive assistance experience agnostic to the specific assistance visual representation and implementation.

Our experiment involved three levels of ASSISTANCE:

- **None** ($k = 1$)**:** No assistance was presented. A target or non-target can be hit if and only if the fingertip collides with the visible physical boundary.
- **Low** ($k = (d + r)/r$)**:** Assistance in this case preempts participants action within one unit of adjacent distance around the center of the target. This aimed to facilitate a local correction process where participants might mis-hit adjacent spheres.
- **High** ($k = (2d + r)/r$)**:** Assistance in this case preempts participants action within one unit of adjacent distance around the center of the target. This threshold is fairly large and aimed to facilitate a considerable portion of hand movement besides correction.

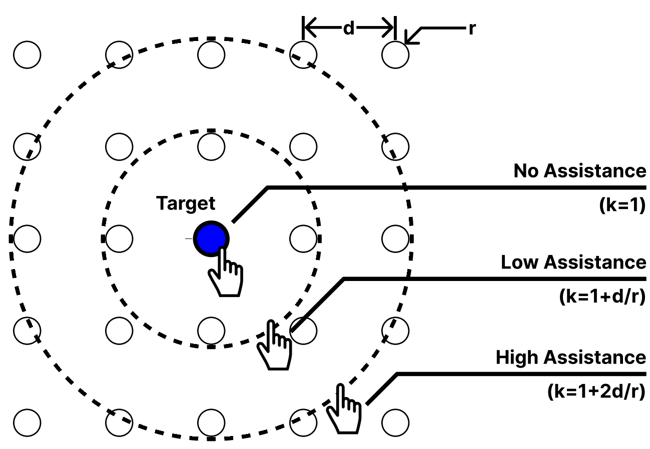


Fig. 5. Assistance mechanism in the experiment. Under *Low* and *High* assistance, participants were able to select a target by positioning their hand at a distance beyond its visible, physical boundary.

B. Interval Estimation

As discussed in Section II-B, our experiment involved interval estimation as a quantitative measure of SoA. After hitting the target (action), participants were presented with a beep sound after a randomized time delay (outcome). Participants were then prompted to estimate the time between hitting the target and perceiving the beep sound, before moving on to the next trial. Similar to [26], we used three fix intervals: 150 ms, 400 ms, and 700 ms. Participants are told that the beep interval is fully random and that it ranges from 50 ms to 950 ms in steps of 50 ms. Each of the three intervals was randomly repeated 10 times per condition.

After the trial, a panel would pop up in the same virtual environment to collect participants' interval estimation. Participants use a controller in their non-dominant to give their estimation, pressing the joystick left and right to toggle between interval options and the index trigger button to confirm, before moving on to the next trial.

C. Measurements

We recorded participants' task performance data, SoA (interval estimation and questionnaire), and users' behavioral data.

Performance: We recorded the average *target pointing time* and *error count* of participants in each conditions. *Target pointing time* refers to the time it took the participants to leave the reset cube and first hit the target in a successful selection. *Error count* refers to the number of incorrect touches participants made to non-targets.

Interval Estimation Error: We recorded the average *interval estimation error* participants made in each conditions. *Interval estimation error* refers to the difference between the estimated interval (50 ms to 950 ms in steps of 50 ms) and the actual interval(150 ms, 400 ms, and 700 ms).

Agency Questionnaire: Complementary to the interval estimation error, we also adopted the agency questionnaire [6] inquiring about participants' subjective experience in each condition (after a continuous period). This questionnaire includes 13 questions, targeting both the sense of positive and negative agency, as provided in the supplementary materials.

Behavioral Data: We also logged participants' behavioral data for secondary analysis to make sense of primary results. With logging of the participants' index pointer trajectory, we derived *selection distance ratio*, defined by the distance to the target divided by the actual distance threshold (range) in assisted selection, and *selection speed*, defined by the speed of participants' index finger at selection. Both *Selection distance ratio* and *selection speed* give clues of how aware the participants were about the implicit assistance and exploit it.

D. Experimental Design

Our experiment examines the impact of two independent variables: ASSISTANCE (3 levels: *None*, *Low*, *High*) and DIFFICULTY (2 levels: *Easy*, *Hard*) on participants' SoA and performance. This combines to a total of 6 conditions. In a within-subject design, participants went through all 6 conditions. To mitigate the ordering effects, we counterbalanced the order using a Latin Square, resulting in 6 possible orders. The 12 participants used all conditions twice. We analyzed ORDEReffects (e.g., 5 levels, condition order, between-subject) and did not find a main effect of order on any of our dependent variables (all $p > .05$).

E. Experimental Procedure

After obtaining informed consent from the participants, the experimenter first introduced them to the study, equipment, and recorded data. Participants then completed a pre-questionnaire to assess their experience with VR and video games, their state of alertness, and their demographic profile.

Prior to the experiment trials, participants took two brief training sessions. In the first session, participants were brought into the same virtual environment as the actual task without the spheres. They held a controller in their non-dominant hand and pressed the index trigger button to trigger a beep after an interval varied truly randomly between 50ms and 950ms. They estimated the interval between pressing the button and hearing the beep. They were then told the actual interval. This session aimed to familiarize participants with the interval estimation procedure, provide them with a better sense of the brief intervals, and reinforce their expectation that the experimental trials would also involve randomized delays. Participants completed a minimum of 12 trials and exited upon feeling confident. The average estimation offset within the last five trials across all participants was less than 100 ms. In the second session, participants familiarized themselves with the actual target selection task and interval estimation. They performed 5 trials. There was no ASSISTANCE in the practice trials and the choice of DIFFICULTY level was randomized.

Subsequently, participants proceeded through the conditions of our within-subject design. Each condition contains 30 trials, where participants first performed target selection at the designated ASSISTANCE and DIFFICULTY levels, and then provided their estimation of the perceived interval between their action and outcome. After each condition, participants reported their subjective SoA experiences in a post-condition survey. Between conditions, participants were allowed to rest for as long as they preferred. Before exiting the study, we debriefed participants on their experiences, discussing their perceived differences between conditions and the stressfulness after completing the tasks. The entire procedure took approximately 60 min per participant.

F. Apparatus

Participants performed all tasks in a designated experimental space (Figure 3). They were seated at a table ($1.5\ m \times 0.8\ m \times 0.8\ m$) which allows for rest periods between trials to prevent fatigue. We included a virtual representation of the table in the virtual scene. To increase realism, a calibration procedure is performed before each condition to align the virtual and actual/physical table surfaces.

Participants were equipped with a Meta Quest 2 headset, one of the most popular commercial VR headsets [47]. Using Meta XR Interaction SDK 65.0.0, we enabled real-time hand-tracking which presented hand visuals in the virtual scene adjusted to each participant's actual hand size with default material. Participants used their dominant hand for target selection and held a controller in their non-dominant hand for interval estimation. The experiment ran on an Intel Core i7-12700H CPU 2.30 GHz computer with 16 GB of RAM, supported by an NVIDIA GeForce RTX 3060 GPU. The virtual scene was developed using Unity 2021.3.32f1.1.

G. Power and Experimental Participants

Prior to conducting our study, we ran an a priori power analysis using G* Power 3.1 [48] to determine an appropriate sample size. We chose two effect sizes, f = 0.25 and f = 0.5, corresponding to small and medium effect sizes, respectively, to determine the appropriate range for the sample size. We set an alpha error probability of $\alpha = 0.05$ and a power of $\beta = 0.8$. Since each condition consists of 30 trials (for *target pointing time*, *error counts*, and *interval estimation* respectively), we tested setting the number of measurements in G* Power to 180 (6 conditions). The number of groups was dependent upon the within-subject factors, which, in the case of our experiment, was 6. Finally, the correlation among repeated measures was left at the default value of 0.5. The power analysis revealed that we would need 12 participants to obtain a medium effect size. We also considered prior similar experiments (e.g., [20]), which had a similar number of participants.

We recruited 12 participants via snowball sampling starting from university message groups and social networks. Participants had to be 18-70 years old, without significant auditory, visual, or upper limb motor impairments that would disrupt their experience of a VR application. Participants received $15 as gratuity for their time. In the pre-questionnaire, we asked participants to report their demographic information, prior experience with VR (7-point Likert scale, from 1-none to 7-expert), frequency of playing video games (from 1-never to 5-at least once a week), and level of alertness using the Stanford Sleepiness Scale (from 1-active, vital, alert, or wide awake to 7-sleep onset soon). All participants (age: $M = 27$ $years\ old$, $SD = 5$ $years\ old$; 6 female, 6 male) reported normal or corrected-to-normal vision and normal hearing. Participants' median responses were VR experience = 3, gaming frequency = 2, and level of alertness = 3. All participants are right-handed.

IV. Results

We analyzed the effects of ASSISTANCE and DIFFICULTY on participants' performance, sense of agency, and target selection behavior. We then analyzed the relationship between dependent variables using Spearman correlations.

The interval data (performance: *target pointing time*, *error counts*; sense of agency: *interval estimation*; target selection behavior: *selection distance ratio*, *selection speed*) was analyzed using a two-factor repeated-measures multivariate ANOVA. The ordinal data (sense of agency: *agency questionnaire*) was analyzed using an Aligned Rank Transform (ART) ANOVA [49]. Initial checks showed that the interval data did not follow a normal distribution for all independent variables in at least one group (Shapiro-Wilk test $p < .05$). We thus corrected this by transforming the data using log functions. The data after transformation met the sphericity assumption (Mauchley's test $p > .05$ for all variables). For each data value, the *participant* was considered as a random factor, with ASSISTANCE (3 levels: *None*, *Low*, *High*) and DIFFICULTY (2 levels: *Easy*, *Hard*) considered as within-subject independent variables. We used pairwise comparisons with Bonferroni correction to further investigate the main effects resulting from the interaction. As we are interested in understanding the effect of ASSISTANCE at different levels of DIFFICULTY, we performed pairwise comparisons with Bonferroni correction on each value to investigate the simple main effects of ASSISTANCE at different levels of DIFFICULTY regardless of whether there was a main effect of interaction. The statistical analysis was performed using IBM SPSS 29 [50].

A. Performance

All the performance results are shown in Figure 6.A.

Target pointing time: The ANOVA analysis showed a significant main effect of DIFFICULTY ($F_{1,11} = 14.67$, $p < .01$, $\eta_p^2 = .57$) and ASSISTANCE ($F_{2,22} = 77.34$, $p < .001$, $\eta_p^2 = .88$). Participants in *Easy* conditions were faster in pointing the target than in *Hard* conditions (by 22.29%). Compared to *None* assistance, participants were faster under both *High* assistance (by 44.82%, $p < .001$) and *Low* assistance (by 30.59%, $p < .001$). While there was no main effect of interaction, simple main effects showed that the effect of ASSISTANCE was different at different DIFFICULTY levels: while in both *Easy* and *Hard* conditions a *High* assistance led to significantly faster performance than with *None* assistance ($p < .001$), only in *Hard* conditions did *High* assistance lead to a significantly improved time than *Low* assistance (by 27.31%, $p < .01$).

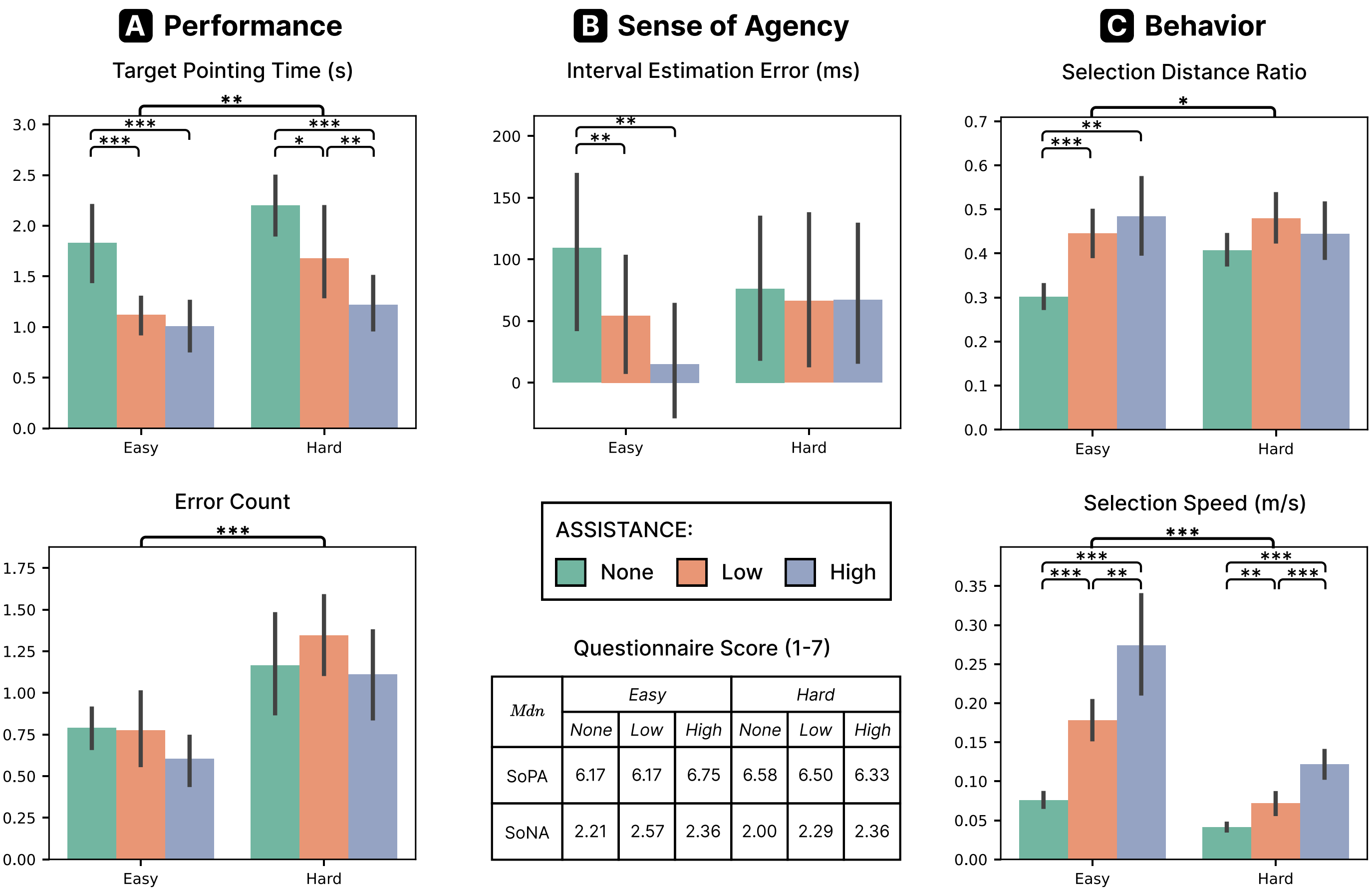
Error counts: The ANOVA analysis showed a significant main effect of DIFFICULTY ($F_{1,11} = 20.96$, $p < .001$, $\eta_p^2 = .66$). Participants exhibited fewer selection errors in *Easy* conditions than *Hard* conditions (by 39.97%). The ANOVA analysis also showed a significant main effect of ASSISTANCE ($F_{2,22} = 4.61$, $p = .02$, $\eta_p^2 = .30$). No additional effect was observed in pairwise comparisons.

B. Sense of Agency

The results are shown in Figure 6.B.

Interval Estimation: No effect was shown of DIFFICULTY. A significant main effect of ASSISTANCE was shown ($F_{2,22} = 4.99$, $p = .02$, $\eta_p^2 = .31$). Pairwise comparisons showed no additional effects. Notably, a significant effect of interaction was observed ($F_{2,22} = 4.60$, $p = .02$, $\eta_p^2 = .30$). Subsequent pairwise comparisons showed that in *Easy* conditions, participants would give a lower interval estimation under *High* assistance (mean difference 94.06 ms, $p < .01$) and *Low* assistance (mean difference 54.80 ms, $p < .01$) compared to *None* assistance, indicating a higher sense of agency. This effect was not observed in *Hard* conditions.

Agency Questionnaire: The ART analysis showed no main effect or simple main effect of ASSISTANCE, DIFFICULTY, or their interaction on the combined scores, i. e., the sense of positive agency (SoPA) and the sense of negative agency (SoNA), or any individual subjective ratings.



Mdn	*Easy*			*Hard*		
	None	*Low*	*High*	*None*	*Low*	*High*
SoPA	6.17	6.17	6.75	6.58	6.50	6.33
SoNA	2.21	2.57	2.36	2.00	2.29	2.36

Fig. 6. Effects of DIFFICULTY and ASSISTANCE on (A) Performance, (B) Sense of Agency, and (C) Behavior. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$.

C. Target Selection Behavior

The results are shown in Figure 6.C.

Selection Distance Ratio: The ANOVA analysis showed a significant main effect of DIFFICULTY ($F_{1,11} = 7.72$, $p = .02$, $\eta_p^2 = .41$), ASSISTANCE ($F_{2,22} = 10.93$, $p < .001$, $\eta_p^2 = .50$), and their interaction ($F_{2,22} = 12.77$, $p < .001$, $\eta_p^2 = .54$). Participants exploited the affordance more in *Hard* conditions than in *Easy* conditions (by 8.29%, $p = .02$). Compared to *None* assistance, participants exploited the affordance more under *High* assistance (by 31.07% $p = .03$) as well as *Low* assistance (by 30.51%, $p < .01$). Notably, in *Easy* conditions, participants exploited the affordance more under *Low* assistance (by 47.35%, $p < .001$) and *High* assistance (by 60.26%, $p < .01$) compared to *None* assistance. This effect was however not observed in *Hard* conditions.

Selection Speed: The ANOVA analysis showed a significant main effect of DIFFICULTY ($F_{1,11} = 635.43$, $p < .001$, $\eta_p^2 = .98$), ASSISTANCE ($F_{2,22} = 89.76$, $p < .001$, $\eta_p^2 = .89$), and their interaction ($F_{2,22} = 5.28$, $p = .01$, $\eta_p^2 = .33$). At the moment of selection, participants moved their index fingers faster in *Easy* conditions than *Hard* conditions (by 125.64%, $p < .001$). Compared to *None* assistance, participants moved their index fingers faster under *High* assistance (by 241.38%, $p < .001$) and *Low* assistance (by 115.52%, $p < .001$). All pairwise comparisons for the simple main effect showed a significant difference where the selection speed was highest under *High* assistance, followed by *Low* assistance, and then *None* assistance.

D. Correlation Analysis

We further analyzed how dependent variables in Performance, Sense of Agency, and Target Selection Behavior were correlated with each other. We calculated the Pearson correlation coefficient between each variable normalized previously with the log transformation, on all data and data split by DIFFICULTY levels. The results are shown in Figure 7.

Overall, the correlation coefficients between most of the variables were insignificant ($p > .05$). There is a strong negative correlation between Target Pointing Time and Selection Speed for all data and data from both *Easy* and *Hard* conditions (all $\rho < -0.70$, $p < .001$). A weak negative correlation was shown between Error Count and Selection Speed for all data ($\rho = -0.24$, $p = .04$). In *Easy* conditions, there was a weak negative correlation between participants' interval estimation error and selection distance ratio ($\rho = -0.37$, $p = .03$).

V. Discussion

We conducted a 12-participant experiment that empirically investigated the relationship between task performance and

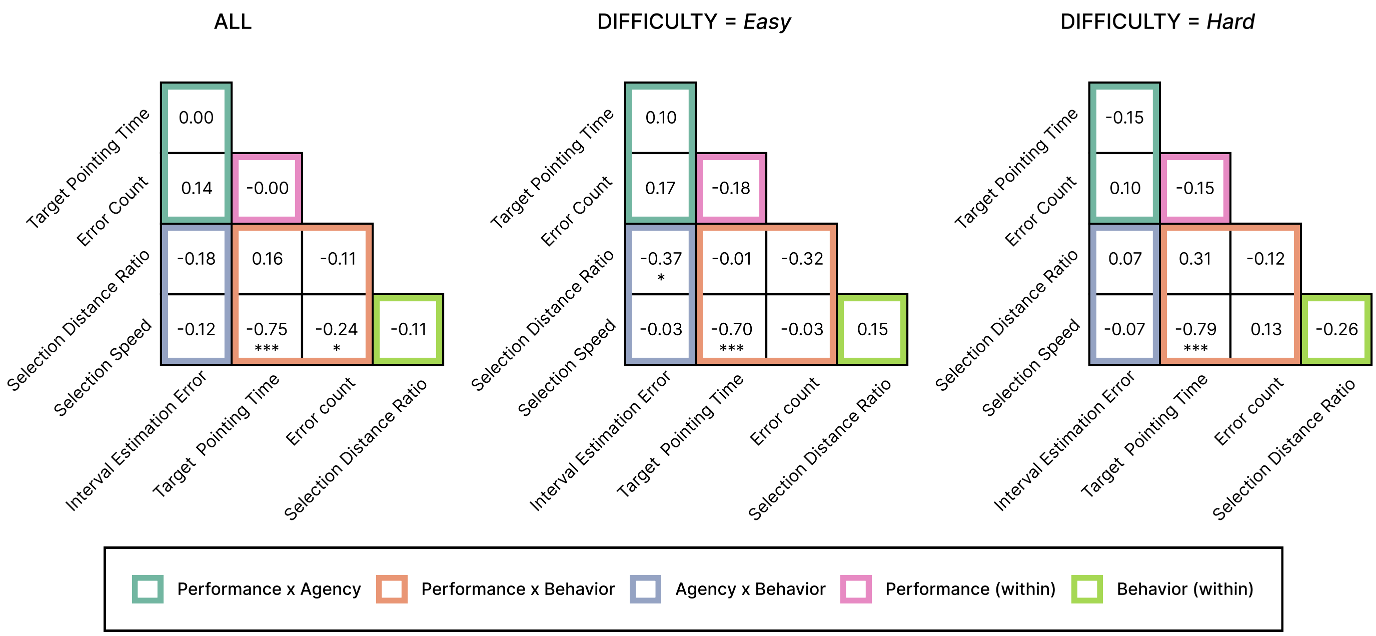


Fig. 7. Pearson correlation coefficients for Performance, Agency, and Behavior variables. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$.

SoA in a target selection task, under varying levels of ASSISTANCE that preempts the trigger of selection and varying task DIFFICULTY. The results revealed variances in consequent task performance, SoA, and behavior. In this section, we provide a deeper analysis of these findings to address the research questions posed earlier. We then propose guidelines for the design of intelligent target selection assistance, concluding with a discussion on our limitations and future directions.

A. RQ1: Does Performance "Trade Off" Agency?

Contrary to the commonly held belief that assistance correlates with SoA decrease, our study showed that, while enhancing participants' task performance, providing preemptive assistance did not diminish SoA. Across all conditions, increasing the level of preemptive assistance, i. e., the preemptive gain applied for expanding the (invisible) selection boundary, improved performance by reducing target pointing time. However, this performance boost did not result in any significant changes in SoA, as measured by both interval estimation and questionnaires. Additionally, our correlation analysis revealed no significant relationship between any performance metrics and SoA measures. These findings suggest that, in our task scenario, optimizing performance does not come at the cost of a diminished SoA. In other words, designing target selection interaction techniques with intelligent preemptive assistance can aim to primarily improve performance without worrying about potential negative impacts on users' SoA.

Although the main effect of ASSISTANCE on SoA was negligible, interesting trends emerged for SoA measured through interval estimation comparing different task difficulty settings: While remaining constant regardless of the level of ASSISTANCE in the *Hard* conditions, in the *Easy* condition, participants' perceived interval reduced with *Low* or *High* levels of ASSISTANCE compared to no ASSISTANCE, which, according to the intentional binding paradigm, indicates an increase in SoA. This suggests that in scenarios where targets are more easily selectable, a high level of ASSISTANCE could lead to both improved performance and a stronger SoA for *Easy* task settings, although an immediate causal relation between SoA and performance may not exist, since no significant correlation was found between performance metrics (e.g., target pointing time and error count) and SoA. Notably, in our results, the effect of ASSISTANCE on performance and SoA plateaued at *Low* level - no significant difference observed in either target pointing time (and error count) or interval estimation between *Low* and *High* ASSISTANCE levels. This implies that the benefit of assistance in optimizing for performance and SoA is bounded by a reasonable threshold.

B. RQ2: What Factors Might Contribute to Agency?

In this section, we attempt to interpret the causes of the observed variations in SoA and propose potential contributing factors. We structure our discussion around the two theoretical frameworks on the origins of agency (discussed in Section II-A) - *Predictive Model* and the *Postdictive Model*, each corresponding to one of two SoA measures we employed - interval estimation [7] and agency questionnaire. While these discussions are grounded in theory and observations, we acknowledge that many parts of the discussions are hypothetical and derived based on educated assumptions. To understand the intricacy of agency, future work should consider further designing controlled experiments around the factors we propose.

1) Predictive Model & Interval Estimation: The *Predictive Model* posits that SoA arises when participants' sensory feedback loop anticipates the sensory outcomes of their actions. In our experiment, the sensory feedback loop would receive a stimulus at the moment of selection when the target sphere changes its color instantaneously. Due to the preemptive assistance, participants would trigger selection with a margin between their index finger and the visible target boundary. However, they continued moving toward the visible boundary of target spheres, creating a "behavioral offset". This offset thus shifted participants' internal perception of their actions backward, reducing SoA.

This "behavioral offset" was reflected in the behavior metrics, in particular, the selection distance ratio, which turned out to align with interval estimation in its response to ASSISTANCE levels: Not only did both measures show significant differences when comparing *Low* or *High* ASSISTANCE to no ASSISTANCE conditions, but the Pearson correlation analysis revealed a significant negative correlation between selection distance ratio and interval estimation ($\rho = -0.37$, $p = .03$). This also holds for *Hard* conditions, where increased preemptive assistance did not lead to significant differences in either selection distance ratio or interval estimation error.

We thus hypothesize the following: In *Easy* task difficulty conditions, with increasing levels of preemptive assistance, participants would become more attentive and exploit the assistance more. This would result in a higher selection distance ratio, which minimizes participants' "behavioral offset", leading to a more proactive perception of their actions and, consequently, a stronger SoA.

2) Postdictive Model - Agency Questionnaire: We observed consistently high SoA results as measured by the agency questionnaire [6] which follows the *Postdictive Model*, suggesting that SoA is largely constructed from the context of the experience and subsequent reasoning. One key factor contributing to this consistency is the implicit nature of the preemptive assistance mechanisms. During debriefing, some participants ($N = 5$) reported an inability to distinguish the differences among the conditions (e.g., "I feel like they are all the same", P3), indicating a steady subjective experience despite clear differences in objective task performance (e.g., target pointing time and error count). This suggests that the preemptive assistance caused no noticeable loss of agency, as it was seamlessly integrated into the target selection process.

Task performance is another crucial factor that shapes the context of the experiment. Although SoA ratings remained constant despite variations in performance metrics due to ASSISTANCE and DIFFICULTY, we observed that participants maintained consistently high performance throughout the experiment, both in target pointing time (average $m = 1.51s$, $m_{Easy} = 1.32s$, $m_{Hard} = 1.70\ s$) and error count (average $m = 0.97$, $m_{Easy} = 0.72$, $m_{Hard} = 1.21$). During debriefing, all participants ($N = 12$) qualitatively reported feeling low stress and reasonably confident in their performance across conditions. This high level of objective and subjective performance likely fostered a positive retrospective evaluation, contributing to stable SoA across conditions over continuous experiences.

C. Guidelines for Future Design

Based on our findings, we have gained the following insights into designing future target selection techniques in VR that aim to "balance" task performance with SoA with intelligent assistance:

- It could be feasible to enhance performance through intelligent assistance without sacrificing the user's SoA.
- Providing preemptive assistance in easier task configurations of target selection in VR could lead to a more significant increase in the user's SoA.
- The interplay between predictive and postdictive models of agency suggests that a strong SoA can result from both successful outcomes (postdictive influences) and coherent sensory feedback (predictive mechanisms). Future interaction designs should consider integrating elements that enhance both aspects to foster a robust SoA.
- The preemptive assistance mechanism, which extends beyond the immediately visible boundaries for selection triggering, can be integrated into target selection naturally without causing perceptible disruptions, thereby improving task performance.

D. Limitation and Future Work

Our 12-participant experiment explored the relationship between task performance and SoA in a target selection task. The study intentionally prototyped experiences where a positive SoA was elicited by directing participants to choose designated targets. Although participants could initiate their actions at any time, this approach imposed a predefined intention on participants to select the correct target. While useful for precise measurements, it may not fully represent the varied experiences of agency in more dynamic environments. Also, our experiment design always assisted in the selection of a target that aligned with the intention of the participants. This represents ideal conditions that may not reflect the complexities of real-world interactions, where misalignments are common, such as ML systems misidentifying targets or users changing their intentions unexpectedly. Future investigations should thus adopt less controlled experimental designs to explore these non-ideal interactions, providing participants with greater autonomy to formulate and act on their intention as well as misaligned assistance to explore how discrepancies affect SoA (e.g., [51]).

Our study provides empirical support for the feasibility of optimizing target selection performance without compromising SoA in user experience. As an exploratory study, we only investigated only three levels of ASSISTANCE and two levels of DIFFICULTY. Future work could further examine how SoA changes in continuous distributions by designing more fine-grained independent variables. Additionally, while our study is grounded in established theories of agency, it did not account for other factors, such as embodiment [52] and external environment [53], which past research has shown to be critical to the subjective feeling of agency in practical scenarios. Future work should broaden the theoretical framework to include these elements, investigating their role and interplay in shaping SoA.

Finally, extending the relationships and values identified in our study to downstream applications (e.g., accessibility [54]) offers a promising avenue to enhance the reach and relevance of our findings on agency and performance. We hope to tailor our findings to specific applications, addressing unique user needs to drive advancements and expand the practical applications of our research.

VI. Conclusion

We presented the results of a 12-participant empirical study investigating the relationship between task performance and the sense of agency in a target selection task with varying levels of preemptive assistance and task difficulty. We observed that contrary to the belief that improved performance reduces the sense of agency, our study demonstrated that assistance did not diminish the sense of agency. The preemptive gain in assistance, i. e., the distance threshold for triggering selection, when increased, enhanced performance by reducing target pointing time without significantly affecting the sense of agency, as confirmed by both interval estimation and questionnaire assessments. Interestingly, for *Easy* task configurations, the sense of agency measured by interval estimation increased with more preemptive assistance due to more attentive and proactive behaviors. Our results suggest that it is feasible to enhance performance through intelligent assistance without sacrificing the user's sense of agency. Moreover, the interplay between predictive and postdictive models of agency indicates that a robust sense of agency can emerge from both successful outcomes and coherent sensory feedback, suggesting that future interaction designs should integrate elements that enhance both aspects.

In conclusion, our study provides a foundational understanding of how intelligent assistance through preempting selection can be designed to enhance performance while maintaining or even enhancing the sense of agency in target selection tasks. Future research should expand on these findings by exploring less controlled experimental designs and investigating the impact of non-aligned assistance scenarios, as well as incorporating broader agency factors such as embodiment and environmental influences.

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SUPPLEMENTARY MATERIAL

Performance As Agency? Investigating the Trade-off between Sense of Agency and Performance in Preempted Target Selection in Virtual Reality

A1. Pre-questionnaire

Q1 On a scale of 1 to 7, rate your previous experience with Augmented Reality. *[1-none, 7-expert]*
Q2 On a scale of 1 to 7, rate your previous experience with Virtual Reality (e.g., Oculus Quest). *[1-none, 7-expert]*
Q3 How frequently do you play video games? *[1-never played or occasionally, 2-once every 2 or 3 months, 3-once every month, 4-once every 2 weeks, 5-at least once a week]*
Q4 Pick what best represents how you are feeling right now. *[1-feeling active, vital, alert, or wide awake, 2-functioning at high levels, but not fully awake, 3-awake, but relaxed, responsive but not fully alert, 4-somewhat foggy, let down, 5-foggy, losing interest in remaining awake, slowed down, 6-sleepy, woozy, fighting sleep, prefer to lie down, 7-no longer fighting sleep, sleep onset soon, having dream-like thoughts]*
Q5 Do you have any known hearing impairments? If so, please indicate the type of hearing impairment.
Q6 Do you have any known visual impairments? If so, please indicate the type of visual impairment (e.g., color blindness).
Q7 Do you wear contact lenses? *[yes, no]*
Q8 Do you wear glasses? *[yes, no]*
Q9 Do you have any known upper-body motor impairments? If so, please indicate the type of hearing impairment.

Q4 is drawn from Shahid et al. [55].

A2. Post-condition Agency Questionnaire

The following questions are drawn from Tapal et al. [6].

Q1 I am in full control of what I do. *[1-fully disagree, 7-fully agree]*
Q2 I am just an instrument in the hands of somebody or something else. *[1-fully disagree, 7-fully agree]*
Q3 My actions just happen without my intention. *[1-fully disagree, 7-fully agree]*
Q4 I am the author of my actions. *[1-fully disagree, 7-fully agree]*
Q5 The consequences of my actions feel like they don't logically follow my actions. *[1-fully disagree, 7-fully agree]*
Q6 My movements are automatic—my body simply makes them. *[1-fully disagree, 7-fully agree]*
Q7 The outcomes of my actions generally surprise me. *[1-fully disagree, 7-fully agree]*
Q8 Things I do are subject only to my free will. *[1-fully disagree, 7-fully agree]*
Q9 The decision whether and when to act is within my hands. *[1-fully disagree, 7-fully agree]*
Q10 Nothing I do is actually voluntary. *[1-fully disagree, 7-fully agree]*
Q11 While I am in action, I feel like I am a remote-controlled robot. *[1-fully disagree, 7-fully agree]*
Q12 My behavior is planned by me from the very beginning to the very end. *[1-fully disagree, 7-fully agree]*
Q13 I am completely responsible for everything that results from my actions. *[1-fully disagree, 7-fully agree]*