Effect of Distractor on Temporal Target Selection

Jae-Yeop Jeong
Department of Data Science
Seoul National University of Science and Technology
South Korea
jaey.jeong@seoultech.ac.kr

Jin-Woo Jeong*
Department of Data Science
Seoul National University of Science and Technology
South Korea
jinw.jeong@seoultech.ac.kr

Abstract

Distractors have traditionally been regarded as problematic elements in graphical user interfaces. Interestingly, however, in interactive games, distractors are often deliberately employed as design elements to create novel and engaging scenarios. Among the various characteristics of distractors, prior research has primarily focused on their spatial aspects. In contrast, studies on their temporal effects remain limited. This paper investigates how distractors influence user behavior and performance in temporal target selection, defined as selecting a target within a limited time window. Such interactions are commonly encountered in game scenarios, such as shooting games involving moving targets. We empirically studied the impact of the temporal distractor — including temporal distance, width, and departure position — on temporal target selection. Additionally, we derived a predictive model for user performance and evaluated it in a controlled and uncontrolled experiment. We believe our research findings will assist interactive game designers and developers in testing their designs.

CCS Concepts

• **Human-centered computing → Pointing**; **Empirical studies in interaction design**; **Empirical studies in HCI**.

Keywords

Temporal pointing, distractor effects, endpoint distribution, user behavior

ACM Reference Format:
Jae-Yeop Jeong and Jin-Woo Jeong. 2018. Effect of Distractor on Temporal Target Selection. In *Proceedings of Make sure to enter the correct conference title from your rights confirmation emai (Conference acronym 'XX)*. ACM, New York, NY, USA, 15 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

Selecting an unintended target (hereafter, *distractor*) is a common error in classical graphical user interfaces (GUIs). Unsurprisingly, the distractor has been widely recognized as a problematic factor in various operations in the GUI, such as crossing [25], touch-pointing [30, 31, 33], and steering [34, 37]. However, for the design of interactive games, introducing distractors could elicit novel scenarios [7]. For instance, users can engage in high-difficulty shooting games, such as firing at opponents who are partially obscured by obstacles (e.g., trees acting as the distractor) beyond user errors. To design optimal user interfaces (UIs), user performance (e.g., error rates and completion time) predictive models have actively been researched in distractor scenarios [25, 34, 37]. Although these studies focus on relatively classical GUIs, they are quite applicable to the presence of the distractor in interactive games. Nevertheless, the existing research on the distractor is limited in the spatial dimension, and research on the temporal distractor is scarce. This gap raises questions for designers and developers about how the distractor's design (e.g., speed and size) should be considered in temporal target selection to provide an optimal user experience for end-users. Here, we thus explore the effect of the distractor on temporal target selection.

Temporal pointing is a fundamental task in human-computer interaction (HCI). In temporal pointing, users must make a discrete input event (e.g., button input) for a bounded time window to interact with temporal interaction contexts [16]. Many efforts have been made to model performance like error rates and understand user behavior through endpoint distribution in temporal pointing-based tasks [8, 13, 15–17, 19, 39]. Performance prediction models and insights into user behavior in temporal pointing could improve the design and user experience of many applications [8, 21], such as games where precise timing is crucial [13, 19, 39], input device development and evaluation [14], and so on. One of the most important tasks in temporal pointing is temporal target selection. A typical scenario is a game, illustrated in Figure 1(a), in which users are firing a bullet (i.e., pink cursor) at a moving balloon (i.e., blue target). Yu et al. [39] conceptualized this interaction through several task parameters called temporal factors. In detail, to successfully hit the balloon, it is necessary to consider both the time for the balloon to come to a selectable area (i.e., temporal distance (D_t)) and the time the balloon spends in that area (i.e., temporal width (W_t)), as well as the time it takes for the bullet to travel (i.e., expected delay (R_t)). For example, if the target starts moving at $t = 0$, it reaches the selectable area at $D_t = 0.75$s and remains there for $W_t = 0.125$s. Users who have a cursor moving for $R_t = 0.2$s to the selectable area must make an input event within the time window of $[D_t - R_t, D_t - R_t + W_t] = [0.55, 0.675]$ (s) to successfully select the target [39]. Therefore, it is crucial to trigger input within a bounded time window in temporal target selection. It is important to note that this form of temporal target selection differs from typical spatial target selection tasks in HCI. Users continuously observe the moving target and decide when to trigger the input, and thus the input timing is guided by visual information. However, users do not continuously control the cursor trajectory after triggering the input.

*Corresponding author

Conference acronym 'XX, Woodstock, NY

ACM ISBN 978-1-4503-XXXX-X/18/06
https://doi.org/XXXXXXX.XXXXXXX

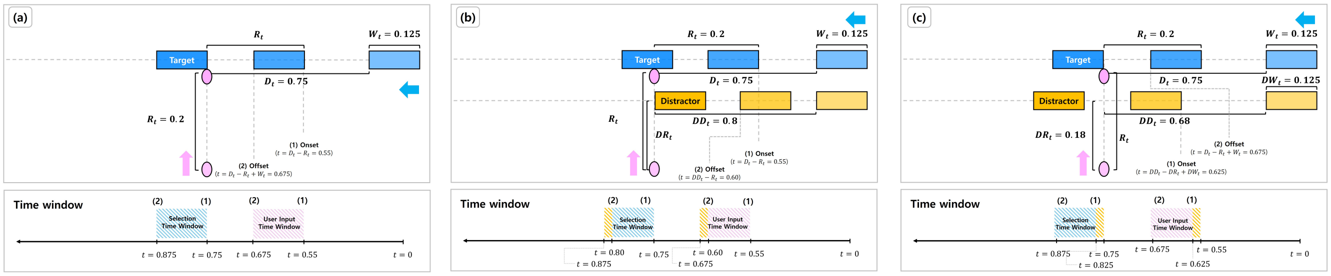

Figure 1: Illustration of temporal target selection under the distractor condition and selection criterion. Blue and yellow squares represent the target and the distractor, respectively. The pink circle represents a cursor that explicitly moves the user toward the target. (a): In standard temporal target selection, the selection criterion is determined by temporal factors of the target only. However, when $D_t < DD_t$ ((b)), the offset of the selection criterion is affected by the distractor. In the case of the $D_t > DD_t$ ((c)), the onset is influenced by the distractor.

Once the input is made, the cursor moves toward the selectable area with a fixed duration and trajectory, without online correction. In this sense, the task can be understood as a trigger-based form of temporal target selection, rather than a conventional pointing task with continuous cursor control and corrective movement.

Interestingly, as we mentioned above, some unintended targets are frequently presented in interactive games, which could affect a bounded time window. For instance, consider a scenario where a bird flies near the balloon, users need to fire a bullet while avoiding hitting the bird (i.e., yellow distractors as illustrated in Figure 1 (b-c)) by considering the bird's temporal factors. This temporal distractor can negatively influence users' attention and internal clock since they distort recognition of movements in both the intended target and cursor. Even minimal temporal overlap between the target and distractor can affect the selectable area physically; in turn, a range of bounded time windows is shortened. This paper, therefore, empirically explores temporal target selection with the distractor to understand user behavior and performance. To this end, we conducted a controlled user study ($N = 12$) similar to [39], yet including two distractor temporal factors and one spatial factor: distractor's temporal distance (DD_t), temporal width (DW_t), and departure position (DP), as illustrated in Figure 1. Through analysis of interaction data, we explored how distractor factors (DD_t, DW_t, and DP) affect the user behavior and performance for temporal target selection. Afterward, we presented a novel error rate predictive model on temporal target selection with the distractor. Furthermore, we evaluated whether the same model structure can characterize user performance in two additional scenarios through uncontrolled user studies. Our contributions are as follows:

- We provide new insights into temporal target selection with the distractor: depending on the distractor's design parameters, such as DD_t, DW_t, and DP, user behavior and performance changed considerably.
- We developed a novel error rate prediction model for distractor scenarios in temporal target selection under fixed target-timing settings.
- We evaluated the model structure in additional scenarios, including new distractor directions and a game-based interface, through uncontrolled user studies.
- We provide design takeaways showing how these parameters can be used as difficulty-control factors in timing-based interaction scenarios, particularly games involving moving targets and obstacles.

2 Problem Space

To understand the details of the temporal target selection task with the distractor, we revisit the concept of temporal target selection without the distractor introduced in [39]. They defined task parameters as follows: *temporal distance* (D_t), *temporal width* (W_t), and *expected delay* (R_t). As illustrated in Figure 1(a), the task goal is to collide the target, where the moving target arrives at D_t and remains for W_t, with the cursor. To this end, users have to produce the input event within a limited time window such that the cursor collides successfully with the target in the *selectable area*. The selection criterion is defined as the interval of time during which a successful selection event can be made. The metric for successful selection is $[D_t - R_t, D_t - R_t + W_t]$ (hereafter, *baseline criterion*). If the distractor is introduced, additional task parameters emerge as follows: *distractor temporal distance* (DD_t), *distractor temporal width* (DW_t), and *departure position* (DP). The distractor reaches the selectable area at time DD_t from either the same or the opposite DP as the target and remains there for DW_t. These additional factors potentially influence a selection criterion; in turn, different user behavior and performance are expected.

2.1 Relationship of Temporal Factors between Target and Distractor

To define our problem space, we first identify conditions outside the scope of our experiment: (1) The distractor is much faster than the target ($D_t >> DD_t$), leaving the selectable area before the target arrives. (2) The distractor is much slower than the target ($D_t << DD_t$), entering the selectable area after the target has left. (3) The distractor is so dominant that selection is impossible (i.e., $W_t << DW_t$). (4) Two separate, non-overlapping time windows for successful selection exist, which represent a more complex case beyond the scope of this initial work. Other out-of-scope conditions are also denoted in Section 6.2.

Our experiment only considers cases where the distractor's temporal parameters substantially affect the target's successful selection window. To verify this, we mathematically check the overlap between: $[t_{target,start},\ t_{target,end}] = [D_t,\ D_t + W_t]$ and $[t_{distractor,start},\ t_{distractor,end}] = [DD_t,\ DD_t + DW_t]$. A valid condition exists when these intervals partially overlap. Through this process, we ensure that only distractor parameters (DD_t, DW_t) that meaningfully interact with the target's temporal factors (D_t, W_t) are included in our experiment.

2.2 Selection Criterion for Temporal Target Selection with Distractor

Unlike the baseline criterion from [39] (see Figure 1(a)), ours naturally depends on DD_t. Based on our problem space, we define two successful criteria for conditions in $D_t < DD_t$ and $D_t > DD_t$. In this study, we do not discuss the condition of $D_t == DD_t$, which serves as an exceptional difficulty when the target and distractor have similar temporal widths. First, when the distractor reaches the selectable area after the target (i.e., $D_t < DD_t$), the successful criterion is defined as $[D_t - R_t, DD_t - R_t]$ as shown in Figure 1 (b). The onset (start time of the selectable time window) is equivalent to the onset of the baseline criterion since the target arrives first. However, before the target leaves, the distractor comes to the selectable area and prevents users from utilizing the all tolerance from W_t. For offset (end time of selectable time window), we need to additionally consider the cursor collision time with the distractor (*expected delay for distractor* (DR_t) in Figure 1(b-c)). A collision with the distractor occurs at the moment DR_t after the cursor has departed, since the position of the distractor is naturally closer to the cursor in terms of spatial distance than the target. Therefore, for successful target selection, users ponder the remaining time after passing the distractor for cursor traveling (i.e., $R_t - DR_t$). Since R_t and DR_t were fixed in our task design, we only considered conditions in which a valid successful window existed after accounting for the remaining travel time from the distractor to the target. In conclusion, our criterion for $D_t < DD_t$ has naturally this characteristics through $DD_t - DR_t - (R_t - DR_t) = DD_t - R_t$.

Another situation is that the distractor reaches the selectable area before the target (i.e., $D_t > DD_t$) as illustrated in Figure 1(c). In this case, successful selection is possible during the interval between after the distractor is non-selectable ($DD_t - DR_t + DW_t$) and before the target's exit from the selectable area ($D_t - R_t + W_t$). To sum up, the offset corresponds to the baseline condition, and the distractor determines the onset, resulting in the following selection criterion: $(DD_t - DR_t + DW_t, D_t - R_t + W_t]$.

For the lower and upper bounds of successful windows of each condition in $D_t > DD_t$, a valid or invalid DR_t emerges. First, DR_t must be smaller than R_t, since the cursor moves along a straight path and reaches the distractor before the target along the perpendicular axis. A valid DR_t must also satisfy $R_t - DR_t < (D_t + W_t) - (DD_t + DW_t)$, where $R_t - DR_t$ represents the remaining time needed for the cursor to reach the target after passing the distractor. In other words, once the cursor has reached the distractor's location, the target must remain in the selectable area for at least the time required to move from the distractor to the target (i.e., $R_t - DR_t$). For example, with $D_t = 1.0$, $W_t = 0.125$, $R_t = 0.2$, $DD_t = 0.9$, $DW_t = 0.125$, and $DR_t = 0.15$, the bounds of the successful time window are $[0.875, 0.925]$. Here, $(R_t - DR_t = 0.05) < (1.125 - 1.025 = 0.1)$ is valid, allowing the user to avert the distractor and successfully hit the target. In contrast, if $R_t - DR_t = 0.11$ $(0.11 > (1.125 - 1.025 = 0.1))$, the calculated window becomes $[0.935, 0.925]$, making temporal target selection with the distractor practically impossible. Thus, DR_t has a limited valid range for task definition, and in this study, R_t and DR_t were held constant.

3 Related work

This paper covers the temporal target selection and builds the predictive model for user performance. In this section, we review the relevant literature on these topics.

3.1 Time-Pressured Interactions

In interactive systems, time has traditionally been treated as a dependent variable (DV) — for example, completion time — since many systems aim to optimize this metric to ensure efficient interaction. However, when considered as an independent variable, time can significantly influence user behavior and performance. Introducing time as an experimental factor — such as through time penalties or strict time limits — has been shown to cause substantial performance degradation [22, 30, 31]. In classical GUI operations such as pointing, crossing, and steering, user performance is often influenced by the well-known speed–accuracy tradeoff. Some studies have explicitly instructed participants to perform tasks as quickly as possible in order to evaluate throughput and efficiency-related parameters [11, 12, 32]. Under such time pressure, participants tended to make more errors compared to conditions where speed was encouraged but not strictly enforced (i.e., "as quickly as possible" vs. "as accurately as possible"). For temporal pointing tasks, users must generate an input signal within a limited time boundary to perform specific tasks like temporal target selection [8, 15, 16, 39]. As the selectable time window becomes shorter, user performance naturally declines due to the increased demand for rapid reaction. Similar to spatial pointing, a speed–accuracy tradeoff has also been observed in temporal pointing tasks [23]. This paper aims to investigate the influence of distractors on users' performance to operate within a constrained time window. This opens opportunities for optimizing interaction design through predictive models of user performance.

3.2 Distractor Effects for Interactions

The distractor was often considered a negative factor in classical GUIs. Users frequently made errors in difficult scenarios caused by the distractor in pointing [3, 26, 30, 31, 33], crossing [25], and steering [34, 36, 37]. Previous works explored how task-irrelevant distractors affect user motor performance. The presence of such distractors prompted users to adopt careful and sophisticated movements to minimize errors. Moreover, beyond the motor aspects, the distractor also exerts significant cognitive influences [6]. It imposes an additional cognitive load that interferes with attentional focus and decision-making processes. Users must expend extra mental

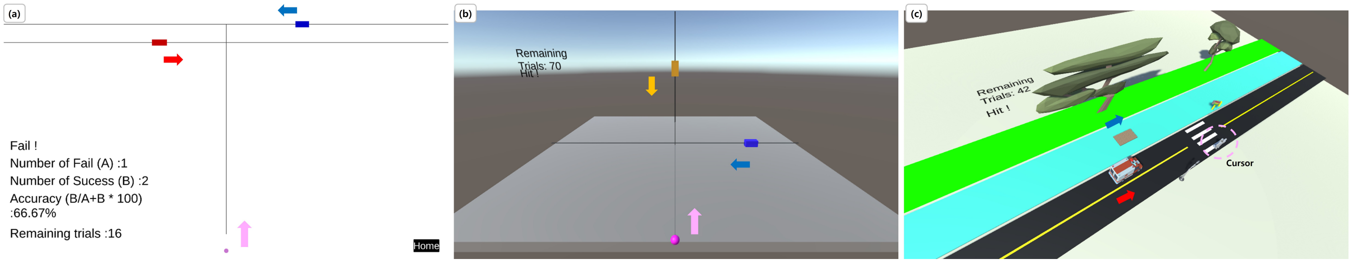

Figure 2: Illustrations of experimental interfaces. (a) participants need to select the blue target using the pink cursor while avoiding the distractor(red) departing from the same or opposite the target. (b) the second experiment has additional distractor departure positions, top and bottom. In the third experiment (c), participants performed temporal target selection in visually complex encoding. The boat, car, and robot correspond to the target, distractor, and cursor, respectively. For more details, please refer to our supplementary video.

effort to filter out the irrelevant distractor, which disrupts their ability to process target-related information efficiently. This cognitive interference can lead to slower reaction times, increased planning time, and even potential shifts in strategy as users try to adjust conflicting visual cues. In effect, the distractor not only demands more precise motor control (or reaction) but also diverts cognitive resources, ultimately compromising overall performance. Our study focuses on the temporal distractor. The distractor is moving toward the selectable area with a target from various directions, which varies the user's selection time window.

3.3 Modeling Target Selection

Modeling target selection has been an active area of research. Early studies primarily focused on one-dimensional (1D) target selection tasks and observed that users' endpoints tend to follow a Gaussian distribution [27, 28]. Leveraging such input distributions, designers, developers, and researchers have aimed to optimize user interfaces to enhance user experience [24, 38], often grounded in target-related factors from Fitts' law [20]. Subsequent work extended the scope from 1D to two- and three-dimensional (2D and 3D) target selection tasks [8, 26, 29, 38], with similar findings that endpoint distributions remain approximately Gaussian. These distributions have allowed researchers to model and predict user performance using relatively simple mathematical formulations [22, 28, 29]. In pointing tasks, users exhibit a speed–accuracy tradeoff [32], and endpoint distributions naturally vary according to users' speed–accuracy preferences [1]. In parallel, growing attention has been paid to modeling user input in the temporal dimension [8, 15, 16, 39]. Unlike spatial tasks, temporal target selection requires users to generate input signals based solely on timing, without any spatial cursor movement. In such tasks, users' input distributions are formed along the time axis (i.e., 1D), which tend to approximate a Gaussian distribution. Temporal input distributions provide valuable insights into user strategies, particularly in time-constrained or dynamic environments. This study seeks to better understand user behavior in a temporal target selection task involving distractors. To this end, we analyze users' input distributions (μ and σ), following the approach of prior research.

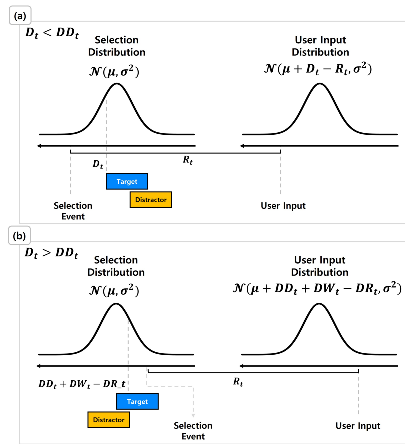

Figure 3: Illustration of relationship of selection distribution and user input distribution under distractor conditions. The selectable area is affected by the distractor.

4 User Behavior and Performance on Temporal Target Selection with the Distractor

Twelve volunteers (7 males and 5 females, mean age 25.25(2.2) years) were recruited from a local university. This sample size is commonly used in the HCI community [4] and exceeds the minimum requirement determined by a G*Power analysis for our experimental setting. All participants were familiar with computer usage and had normal or corrected-to-normal vision. The experimental application was developed using Unity2D with C#. All experiments were performed on a desktop PC, equipped with an Intel Core i7-6900K, a GeForce RTX 4090, and 16GB RAM, with a 27-inch monitor and keyboard used for visualization and input, respectively. The experiment was conducted under approval from the university's ethics board.

4.1 Experimental Design, Task, and Procedure

4.1.1 Experimental design. To examine how the distractor affects user behavior and performance in temporal target selection, we designed an application based on the task described in [39] using the same task parameters. We had two main conditions (hereafter, *baseline*) (unit: s): High-difficulty target setting (HD): $D_t = 0.75; W_t = 0.125; R_t = 0.2$ and Low-difficulty target setting (LD): $D_t = 1.0; W_t = 0.25; R_t = 0.2$. Here, difficulty refers to the baseline temporal target selection setting before introducing distractors. The HD setting has a shorter temporal distance and a narrower temporal width, whereas the LD setting has a longer temporal distance and a wider temporal width [15, 39]. The experiment followed a $3 \times 3 \times 2$ within-subject design structure in each baseline with three independent variables (IVs): $DD_t = \{0.68, 0.8, 0.87\}$, $DW_t = \{0.08, 0.125, 0.16\}$, and $DP = \{SAME, OPPOSITE\}$ for HD and $DD_t = \{0.9, 1.1, 1.2\}$, $DW_t = \{0.125, 0.25, 0.3\}$, and $DP = \{SAME, OPPOSITE\}$ for LD. Additionally, as the baseline, we added no distractor condition in the experiment; in turn, participants interacted with both the within-subject design and baseline condition (i.e., 19 conditions). These task parameters were chosen after evaluating their impact on the target, as discussed in Section 2.1.

Our experiment consisted of two target-setting groups, corresponding to HD and LD. Each target-setting group contained two sessions in a fixed order: 1) practice and 2) main sessions. The order of the two groups was counterbalanced across participants to mitigate potential order effects. In both groups, R_t and DR_t were set as 0.2 and 0.18, respectively, and DW_t, DD_t, and DP were tested in random order together with the baseline. The practice session featured the same task parameters as the main condition to familiarize participants with the actual experimental setup. In the end, from each main session, we logged 1,596 data points (12 participants $\times$ 7 repetitions $\times$ 19 (18 within-subject design + 1 baseline). Figure 2(a) provides the experimental interface in user study 1.

4.1.2 Experimental Task and Procedure. The main task involves using a forward-moving pink cursor to hit a moving blue target while averting a moving red distractor along the horizon. We followed the same scenario and similar color coding as described in the previous work. The cursor, target, and distractor always appeared at the same position in the screen coordinate system. However, depending on DD_t and DW_t, the distractor had different velocities to the selectable area and a width that determines staying time in there. Similarly, based on DP, the initial position of the distractor was reversed.

A selection was deemed successful if the cursor collided with the target while avoiding the distractor. Success was calculated automatically based on the timestamp of the user's input event, eliminating errors caused by system or input device latency. If the target and distractor reached the end of the screen without an input event from the participant, a retrial with the same task parameters was provided. This approach facilitated the participants' rigorous timing by observing the trials multiple times, which enabled us to capture their extreme performance. If an input event occurred, the cursor collided with the target or distractor or moved to the end of the screen, then the screen paused for 0.3 seconds to notice the end of the trial before displaying the following conditions. When a collision was not recognized by the system, participants received textual feedback on the interface indicating success or failure. We recorded interaction data, input time, and error for each trial. No audio feedback was provided during experiments.

Table 1: Result of RM-ANOVA for user study 1.

Cond.	DV	IVs	df_{effect}	df_{error}	F	η_g^2	p
HD	μ	DD_t	1.45	16.01	97.66	.45	<.001
		DW_t	1.56	17.22	21.16	.08	<.001
		DP	1	11	13.07	.10	=.004
		$DD_t \times DW_t$	3.24	35.70	17.22	.18	<.001
		$DD_t \times DP$	1.32	14.61	17.79	.15	<.001
		$DW_t \times DP$	1.68	18.47	1.27	.01	=.296
		$DD_t \times DW_t \times DP$	2.41	26.52	1.41	.01	=.263
HD	σ	DD_t	1.89	20.85	9.14	.06	=.002
		DW_t	1.63	17.99	2.27	.02	=.138
		DP	1	11	29.80	.13	<.001
		$DD_t \times DW_t$	2.21	24.33	1.17	.01	=.329
		$DD_t \times DP$	1.48	16.32	19.90	.08	<.001
		$DW_t \times DP$	1.64	18.13	0.85	.01	=.423
		$DD_t \times DW_t \times DP$	2.72	29.96	1.48	.02	=.239
LD	μ	DD_t	1.28	14.10	96.16	.63	<.001
		DW_t	1.73	19.03	52.39	.18	<.001
		DP	1	11	5.74	.06	=.035
		$DD_t \times DW_t$	3.48	38.32	107.31	.44	<.001
		$DD_t \times DP$	1.39	15.34	31.89	.18	<.001
		$DW_t \times DP$	1.79	19.78	5.32	.02	=.016
		$DD_t \times DW_t \times DP$	3.29	36.22	1.13	.01	=.353
LD	σ	DD_t	1.86	20.52	6.85	.10	<.001
		DW_t	1.67	18.41	0.11	.00	=.860
		DP	1	11	30.90	.15	<.001
		$DD_t \times DW_t$	3.02	33.31	1.23	.02	=.311
		$DD_t \times DP$	1.14	12.62	9.43	.10	=.007
		$DW_t \times DP$	1.80	19.89	2.42	.01	=.119
		$DD_t \times DW_t \times DP$	2.18	23.10	0.62	.01	=.556

4.1.3 Procedure. After we welcomed and greeted a participant, we introduced the background and objectives of our research. We then briefly explained the experimental task. Once verbal consent to participate in the experiment had been obtained, demographics and consent forms were duly collected. They then performed the first target-setting group (i.e., practice and main sessions), followed by the remaining group. We asked participants to perform 100+ trials to experience every within-subject design and familiarize themselves with the experimental setup in a practice session. Participants were welcome to take voluntary breaks as needed between target-setting groups. The distance between the participant and the monitor was set at 70 cm as the default, with the option for the participant to adjust it freely to ensure optimal comfort throughout the experiment. Participants used the *spacebar* on a commercial keyboard to generate input events, allowing them to focus solely on the temporal dimension during target selection. The experiment lasted approximately 20 minutes per participant.

4.2 Results

We analyzed participants' input times using a selection distribution, analogous to the endpoint distribution commonly used in spatial target selection research [8, 9, 22, 26, 38]. For reliable analysis, we first removed outliers in user input time using the three-σ rule. No outliers were found in the baseline, whereas eight outliers (0.5%) were identified in difficulty conditions. All analyses were conducted using Matlab and R. We tested normality using the Kolmogorov-Smirnov (KS) for each condition and then performed a repeated-measure analysis of variance (RM-ANOVA). Statistical significance was assessed at $\alpha < .05$ with generalized-eta square (η_g^2). $\eta_g^2 > .14$

means significant large effect [5]. Table 1 shows the results for our DVs.

4.2.1 Differences in User Behavior. To characterize user behavior, we estimated the mean (μ) and standard deviation (σ) of the Gaussian distribution for each condition using maximum likelihood estimation. Because the effective selectable window changed depending on distractor timing, we adjusted the mean relative to the onset of the valid selection window (see Figure 1). Specifically, for baseline and $D_t < DD_t$ conditions, we computed $\mu_{adjusted} = \mu - D_t + R_t$ (see Figure 3(a)). For the $D_t > DD_t$ conditions, we computed $\mu_{adjusted} = \mu - DD_t + DR_t - DW_t$ (see Figure 3(b)). This adjustment standardizes input timing relative to the onset of the valid selection opportunity, following the logic of prior work [39]. We therefore used two DVs, $\mu_{adjusted}$ and σ.

In HD condition, from 84 data points from baseline ($D_t = 0.75; W_t = 0.125; R_t = 0.2$), we obtained $\mu_{adjusted} = 0.059$ and $\sigma = 0.062$. For μ, the RM-ANOVA revealed significant differences in DD_t, DW_t, and DP, as well as interaction effects between $DD_t \times DW_t$ and $DD_t \times DP$. For σ, we observed significant effects for two IVs (DD_t and DP) and one interaction effect ($DD_t \times DP$). For LD condition, from 84 data points from baseline ($D_t = 1.0; W_t = 0.25; R_t = 0.2$), we obtained $\mu_{adjusted} = 0.128$ and $\sigma = 0.055$. Similar to the results of μ in HD, for LD, we found significant differences in DD_t, DW_t, and DP from RM-ANOVA. Furthermore, we also confirmed several interaction effects of $DD_t \times DW_t$, $DD_t \times DP$, and $DW_t \times DP$. Similarly, for σ, we also observed significant effects in the LD, which were consistent with those found in the HD, for two IVs (DD_t and DP) and one interaction effect ($DD_t \times DP$). Data visualization and details for post-hoc comparisons for μ and σ are provided in Figure 4 and the supplementary material.

4.2.2 Distractor Effect on User Behavior. For both HD and LD, DD_t significantly changed the location of the selection distribution ($\mu_{adjusted}$). When the distractor arrived before the target ($D_t > DD_t$), participants tended to generate inputs shortly after the distractor left the selectable area, producing input distributions that differed clearly from both the baseline and $D_t < DD_t$ conditions. In other words, shorter DD_t shifted the distribution earlier in time (see Figure 4 (a, d)). The distractor width (DW_t) also significantly affected $\mu_{adjusted}$s. As DW_t increased, the distribution shifted earlier (Figure 4 (b, e)), and this tendency was particularly pronounced when $D_t > DD_t$ (see Figure 4 (g, h)). This suggests that when the distractor entered the selectable area first and remained there longer (i.e., long DW_t), participants responded more preemptively to avoid missing the target. Departure position (DP) showed a similar effect. When the distractor originated from the opposite side of the target, participants generated significantly earlier input than when it originated from the same side (see Figure 4 (c, f)). This pattern was especially notable in the $D_t > DD_t$ condition. A plausible explanation is that a fast distractor approaching from the opposite direction imposed a higher perceptual and cognitive load, making it harder for participants to track its temporal relation to the target. As a result, they tended to respond as soon as the distractor left the selectable area. By contrast, some conditions produced distributions similar to the baseline (see Figure 4 (g, h)). In particular, when the distractor arrived later than the target and the effective interference was small ($D_t < DD_t$ and $W_t \leq DW_t$), the resulting interaction more closely resembled standard temporal target selection. Under these conditions, participants could still rely on a timing strategy similar to that used in the baseline.

For the variability of input timing (σ), the overall pattern also depended on distractor timing. In both main conditions, when the distractor arrived before the target ($D_t > DD_t$), participants showed greater timing variability than in the $D_t < DD_t$ condition (see Figure 4 (i, k)). However, the relation to the baseline differed between HD and LD. In HD, the baseline showed a larger σ than the distractor conditions, suggesting that in the absence of a distractor, participants used the full temporal tolerance of W_t more freely. Under distractor conditions, by contrast, they generated more consistent inputs to avoid failure. In LD, the opposite pattern appeared: distractor conditions produced larger σ than the baseline. Unlike $\mu_{adjusted}$, DW_t did not significantly affect σ. Once the target became selectable, participants tended to maintain a similar degree of temporal consistency regardless of distractor width. In contrast, DP significantly influenced σ in both main conditions: opposite-side distractors led to greater variation in input timing than same-side distractors (see Figure 4 (j, l)).

4.3 Modeling User Performance

In this section, we aim to model user performance on temporal target selection, including the distractor. We also sought to see the limitations of existing models, presented in [39], in distractor conditions (see Appendix A). Our models aim to predict the selection distribution and error rate shaped by different distractor conditions. In this study, D_t, W_t, and R_t define the baseline temporal target selection setting, and the model estimates how adding a distractor with DD_t, DW_t, and DP changes users' input timing, input variability, and ER within that setting. We used two baseline settings to examine whether these distractor-driven changes appear consistently across different task difficulties. In this sense, the model is intended to help designers, developers, and researchers evaluate the potential effect of distractors once the temporal target selection setting of an application has been specified.

4.3.1 Model Fitting. Based on the fitting results of existing models, we identified the need for a novel predictive model capable of forecasting user performance under distractor conditions. According to the results of user study 1, we looked at several task parameters of the distractor that affected user behavior (μ and σ) significantly. Therefore, we develop a model for each behavior metric derived with a large magnitude of effect size ($\eta_g^2 > .14$), which means great explanation of results as follows:

$$\begin{cases} \mu = a_1 + b_1 DD_t + c_1 DW_t + d_1 (DD_t \times DW_t) \\ \sigma = a_2 + b_2 DD_t \end{cases} \tag{1}$$

, where a, b, c, and d denote empirically determined regression coefficients. These might be to stand for some noise and individual characteristics during interaction. For μ, we added the interaction effect between temporal parameters ($DD_t \times DW_t$) due to its significant influence in contrast to σ. For σ, we did not see the large effect size in the temporal parameter; therefore, we employed solely DD_t, which had a medium magnitude of effect size ($\eta_g^2 > .10$ [5]).

User behavior and performance varied significantly depending on DP. However, since DP is a categorical variable, incorporating

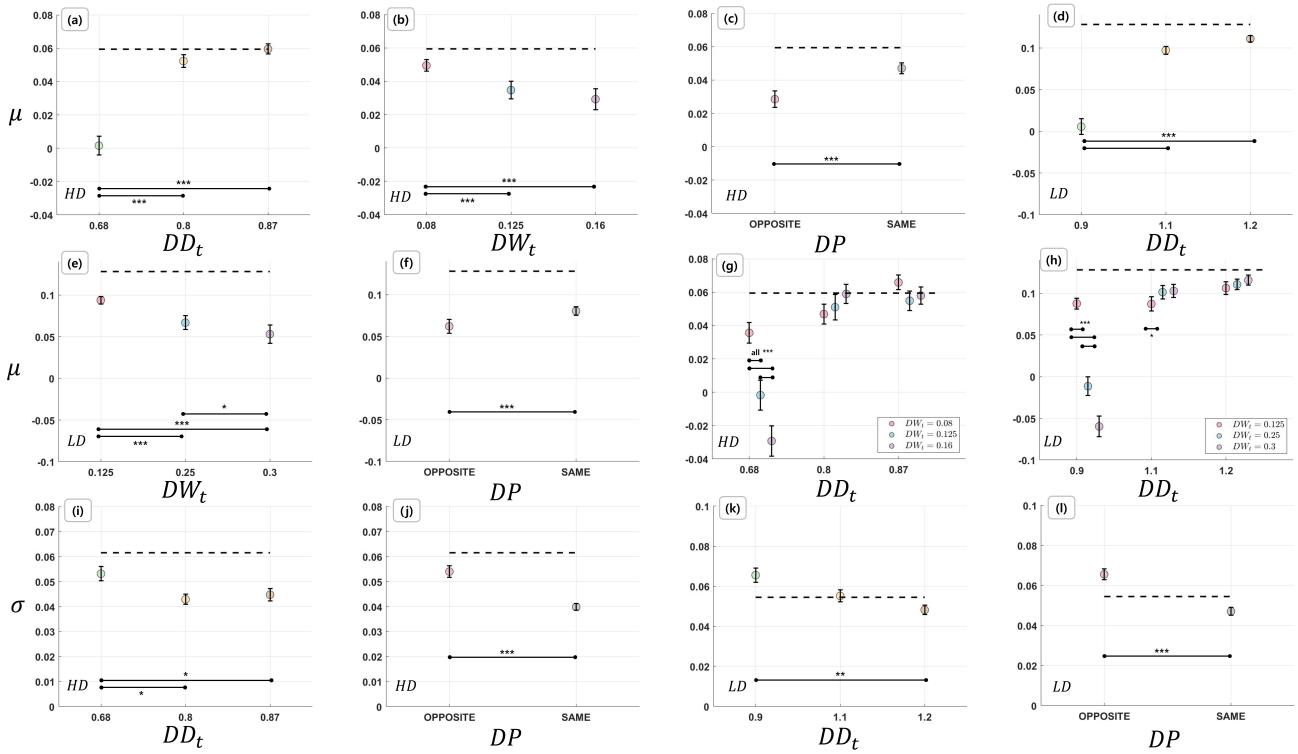

Figure 4: Illustration of selected significant results in the HD ($D_t = 0.75; W_t = 0.125; R_t = 0.2$) and LD ($D_t = 1.0; W_t = 0.25; R_t = 0.2$). (a-c) and (d-f) show results of μ in the HD and LD, respectively. (g) and (h) denote the results of the interaction term ($DD_t \times DW_t$) in the HD and LD, respectively. (i, j) and (k, l) show results of σ in the HD and LD, respectively. Dashed line represents the result of the baseline. Error bars show standard error ($^* = p < .05$, $^{**} = p < .01$, and $^{***} = p < .001$).

Table 2: Model fitting result for DP with nine data points. AIC and BIC are from in-sample goodness-of-fit.

Condition	DP	Selection Mean (μ)				Selection Std. (σ)				Error Rate	
		R^2	MAE	AIC	BIC	R^2	MAE	AIC	BIC	R^2	$MAE(\%)$
HD	$SAME$	0.84(0.07)	0.014(0.006)	-54.01	-53.22	0.15(0.07)	0.003(0.002)	-70.72	-70.33	0.96(0.003)	5.78(0.23)
	$OPPOSITE$	0.88(0.05)	0.019(0.017)	-42.58	-41.79	0.70(0.07)	0.007(0.006)	-59.21	-58.82	0.97(0.010)	3.14(0.65)
	$INTEGRATED$	0.88(0.05)	0.015(0.009)	-49.43	-48.64	0.70(0.07)	0.005(0.003)	-66.91	-66.51	0.97(0.003)	3.68(0.30)
LD	$SAME$	0.93(0.03)	0.022(0.015)	-46.78	-45.99	0.02(0.03)	0.006(0.002)	-64.43	-64.04	0.90(0.010)	6.22(0.51)
	$OPPOSITE$	0.91(0.03)	0.028(0.018)	-35.65	-34.86	0.79(0.04)	0.008(0.004)	-58.49	-58.10	0.97(0.003)	4.43(0.41)
	$INTEGRATED$	0.94(0.02)	0.021(0.011)	-43.34	-42.55	0.81(0.05)	0.006(0.004)	-64.51	-64.11	0.93(0.007)	5.60(0.47)

it directly into a mathematical model (e.g., via one-hot encoding) would substantially increase the number of predictors and complicate interpretation. For instance, if DP had around 20 categories, this would introduce nearly 20 additional predictors. To address this, we fit separate models for each DP, allowing us to evaluate specialized models based on the starting position. More details for DP as an IV are discussed in Section 6.1.2. Additionally, we reprocessed the data across participants for the two starting positions and fitted an integrated model that accounts for both conditions. In other words, for the integrated model, endpoint variables are recalculated across DP. For each model, we have nine data points ($DD_t \times DW_t$) and run linear regressions. We did a leave-one-condition-out cross-validation (LOOCV) to evaluate prediction accuracy (R^2 and MAE) for an untested condition, similar to previous works [35].

4.3.2 Fitting Results. From simple linear regression fitting, we obtained the following results for each DP in HD:

$$Same \begin{cases} \mu = 0.224 - 0.198DD_t - 2.678DW_t \\ \quad + 3.190(DD_t \times DW_t) \\ \sigma = 0.032 + 0.019DD_t \end{cases} \tag{2}$$

$$Opposite \begin{cases} \mu = 0.213 - 0.188DD_t - 4.438DW_t \\ \quad + 5.271(DD_t \times DW_t) \\ \sigma = 0.174^{***} - 0.142DD_t \end{cases} \tag{3}$$

$$Integrated \begin{cases} \mu = 0.230 - 0.206DD_t - 3.591DW_t \\ \quad + 4.264(DD_t \times DW_t) \\ \sigma = 0.130^{***} - 0.092DD_t^{**} \end{cases} \tag{4}$$

Additionally, we also acquired the results of LD for each DP.

$$Same \begin{cases} \mu = 0.506^{*} - 0.367DD_t^{*} - 3.120DW_t^{**} \\ \quad + 2.787(DD_t \times DW_t)^{**} \\ \sigma = 0.052^{*} + 0.003DD_t \end{cases} \tag{5}$$

$$Opposite \begin{cases} \mu = 0.469 - 0.317DD_t - 4.075DW_t^{*} \\ \quad + 3.533(DD_t \times DW_t)^{*} \\ \sigma = 0.206^{***} - 0.119DD_t^{**} \end{cases} \tag{6}$$

$$Integrated \begin{cases} \mu = 0.500^{*} - 0.354DD_t - 3.650DW_t^{**} \\ \quad + 3.206(DD_t \times DW_t)^{**} \\ \sigma = 0.165^{***} - 0.088DD_t^{***} \end{cases} \tag{7}$$

Based on these models, we estimated the error rate using the probability density function of the Gaussian distribution with Equations (18) and (20) to (22). The following section discusses the results of model performance.

4.3.3 Model Performance. Table 2 provides summarized results of modeling fitting, and Appendix C shows correlation plots of in-sample goodness-of-fit between observation and predicted error rate (*ER*). We employed various evaluation metrics, R^2, Akaike's information criterion (*AIC*), Bayesian information criterion (*BIC*), and mean absolute error (*MAE*). Lower *AIC*, *BIC*, and *MAE* indicate better fitting performance.

Overall, the models showed similar fitting trends between the *HD* and *LD* conditions, particularly for μ and *ER*, whereas the fitting performance for σ was less consistent across *DP*. Participants exhibited more consistent behavior under some less demanding distractor conditions, allowing simple linear regression models to effectively capture and predict behavioral metrics. In both conditions, specifically *LD*, model performance was better in the *OPPOSITE* direction than in the *SAME* direction. This suggests that participants employed consistent strategies to achieve higher success rates, as distractors moving in the opposite direction to the target tend to present greater challenges. Interestingly, the poorest model fits for σ were observed in the *SAME* departure position for both conditions, with R^2 values of 0.15 and 0.02, respectively. This is likely because the variation in σ across these conditions was minimal (M = 0.0482, SD = 0.0041, and coefficient of variation ($\frac{\sigma}{\mu}$, CV) = 0.08 for *HD*; M = 0.0562, SD = 0.0054, and CV = 0.09 for *LD*), when compared to the *OPPOSITE* condition (M = 0.0633, SD = 0.0133, and CV = 0.21 for *HD*; M = 0.0790, SD = 0.0167, and CV = 0.21 for *LD*), leaving little meaningful difference for the model to capture. Despite a few exceptions, the models generally achieved strong fitting performance for *ER* in both conditions, including the integrated *DP* condition. This indicates that *ER* can be estimated reasonably well after pooling the tested *DP* conditions. However, this does not mean that *DP* has no effect on user behavior. In particular, the poorest model fits for σ were observed in the *SAME* departure position, suggesting that *DP* should be explicitly considered when modeling input variability. This finding holds potential for more efficient model deployment when the primary goal is to estimate *ER*.

5 Model Evaluation in Novel Scenarios

In this section, we evaluate the generalizability of our models through two uncontrolled user studies conducted in novel settings involving new distractors and game-based scenarios. Through this study, we could assess the robustness of our model in the context of (1) untested distractor conditions, (2) more complex visual encoding, and (3) uncontrolled environments for user playing.

5.1 Novel Distractor from Untested Directions

In user study 1, we examined the effect of *DP* when the distractor moved in the same or opposite direction relative to the target. In the current experiment, we introduce the distractor moving into the selectable area from a novel direction. While the experimental interface closely resembles that of user study 1, we implemented it in 3D to allow for additional distractor entry directions, specifically *TOP* and *BOTTOM*. To support this, we developed a WebGL-based application using Unity3D (see Figure 2(b)). The total movement distance for both the target and the distractor was set to 40 meters in the Unity3D scene space. The cursor and selectable area were positioned at the midpoint of this distance. The primary condition for the target's approach and stay in the selectable area was defined as $D_t = 1.4$ and $W_t = 0.3$ in seconds. For the distractor, the experiment followed a $3 \times 3 \times 4$ within-subject design with three IVs: $DD_t = \{1.3, 1.5, 1.6\}$, $DW_t = \{0.25, 0.3, 0.35\}$ (both in seconds), and $DP = \{\text{SAME}, \text{OPPOSITE}, \text{TOP}, \text{BOTTOM}\}$. Here, appended *DP*s (*TOP* and *BOTTOM*) indicate the vertical direction of the distractor relative to the selectable area. The target always starts from the right of the selectable area. The *DP* conditions used in user study 1 correspond to leftward (*SAME*) and rightward (*OPPOSITE*) distractor movement. For the *BOTTOM* condition, we rendered the floor on which the target moves as translucent, allowing participants to see the distractor as it ascended from below. Participants triggered movement by pressing the *spacebar*, which caused the cursor to move in a straight line toward the selectable area over a fixed duration of 0.2 seconds (i.e., R_t). DR_t was set to 0.189 seconds. We designed the current experiment to provide a slightly lower difficulty level than the *LD* in user study 1 due to the more complex distractor conditions in the 3D. Each condition was repeated ten times, resulting in a total of 360 input events per participant.

5.2 Game-based Interfaces

We developed a WebGL-based application with a visually complex, game-like interface with Unity3D, as illustrated in Figure 2(c). In this task, participants were instructed to make a robot character jump across crosswalks to reach a boat while avoiding moving distractors, represented by oncoming cars. Three car designs were used as distractors: (1) a minivan, (2) a police car, and (3) an ambulance, all of which were sourced from open assets available on the Unity Store. These were categorized by visual size into small, medium, and large distractors, respectively. Participants controlled the robot's jumps using the *spacebar* on a keyboard. In this scenario, the *DP* was fixed to *SAME*, unlike in user study 1, as we anticipated that the *OPPOSITE* condition would result in frequent errors under a visually complex interface. The total movement distance for both the target and the distractor was set to 70 meters in the Unity3D scene space. The robot was positioned at the midpoint of this distance, where the selectable area was located. The jump duration toward the selectable area was set to 0.2 seconds (i.e., R_t), consistent with user study 1, and DR_t was set to 0.153 seconds. We had a main condition for the target (unit: s): $D_t = 1.2; W_t = 0.2$. Additionally, for the distractor, the experiment followed a 3×3 within-subject design structure in two IVs (unit: s): $DD_t = \{1.05, 1.3, 1.39\}$ and $DW_t = \{0.16, 0.2, 0.26\}$. To minimize failures in the complex interface, the overall task difficulty was calibrated to match the LD condition similarly from user study 1. Each condition was repeated twenty times, resulting in a total of 180 input events per participant.

5.3 Participants and Experimental Procedure

5.3.1 Participants. User study 2 was conducted as a crowdsourced online experiment and consisted of two separate scenarios: the novel distractor scenario and the game-based scenario. We recruited eighteen anonymized volunteers for the novel distractor scenario (9 males and 9 females; mean age = 24.56, SD = 1.83) and eighteen anonymized volunteers for the game-based scenario (11 males and 7 females; mean age = 23.77, SD = 2.58) through Google Forms posted in a public board and chat room at a local university. Because no personally identifiable information was collected, we were unable to determine whether any participants took part in user study 1 or whether some participants participated in both scenarios of user study 2, similar to prior crowdsourcing-based work [35]. Therefore, some participant overlap may exist across the datasets. Participants experimented with their desktop PCs or laptops in their designated space.

5.3.2 Procedure. Participants were first asked to read a description of the study thoroughly. If they agreed to participate, they provided minimal demographic information (i.e., age and gender) along with informed consent. They then proceeded to the WebGL-based experiment for each scenario, following on-screen instructions. Detailed guidance was provided regarding the experimental task, interface, and desired behavioral bias (i.e., to perform as accurately as possible). As in user study 1, participants were given multiple opportunities to observe the movement patterns of both the target and the distractor to facilitate optimal performance. Before the main experiment, all participants completed a mandatory practice session. Participants were allowed to repeat the practice session as many times as needed until they felt sufficiently familiar with the experimental interface. Participants could take voluntary breaks as needed after the practice phase. Input events were triggered using the *spacebar* on their personal computers. Each main experiment lasted approximately 20 minutes per participant.

5.4 Modeling and Performance

Similar to user study 1, we fitted the simple linear regressions with nine corresponding fitting points for each scenario. For stable and reliable analysis, we also removed outliers and checked the normality. The following section discusses more details.

5.4.1 Results of Novel Distractor Scenario. In total, we collected 6,480 data points, and we found 66 outliers (1.01%) through a three-σ rule. The mean ER was 56.81(0.23)%. Results from the KS test conducted for each condition per participant indicated that all conditions followed a Gaussian distribution. The model was fitted using the data collected in the current experiment, yielding the following results as shown in Figure 7(a-e) of Appendix D.

$$Same \begin{cases} \mu = 1.044 - 0.627DD_t - 5.576DW_t \\ \quad + 3.644(DD_t \times DW_t) \\ \sigma = 0.089 + 0.009DD_t \end{cases} \tag{8}$$

$$Opposite \begin{cases} \mu = 0.601 - 0.276DD_t - 5.987DW_t \\ \quad + 3.754(DD_t \times DW_t) \\ \sigma = 0.228^{***} - 0.088DD_t^{**} \end{cases} \tag{9}$$

$$Top \begin{cases} \mu = 0.241 - 0.036DD_t - 4.386DW_t \\ \quad + 2.735(DD_t \times DW_t) \\ \sigma = 0.137^{***} - 0.023DD_t \end{cases} \tag{10}$$

$$Bottom \begin{cases} \mu = 0.538 - 0.258DD_t - 5.876DW_t \\ \quad + 3.778(DD_t \times DW_t) \\ \sigma = 0.120^{**} - 0.015DD_t \end{cases} \tag{11}$$

$$Integrated \begin{cases} \mu = 0.588 - 0.285DD_t - 5.380DW_t \\ \quad + 3.419(DD_t \times DW_t) \\ \sigma = 0.570^{***} - 0.041DD_t^{***} \end{cases} \tag{12}$$

Table 3 presents the full results of the current experiment, and all visualizations of model fitting using the entire dataset are provided in Figure 7 (a-f). We observed trends consistent with those found in user study 1. Across the different DP conditions, the model demonstrated high predictive performance in terms of μ and ER. For both the $SAME$ and $OPPOSITE$ directions, the model's fit aligned closely with the results observed in user study 1. Despite the change to a 3D experimental interface, the outcomes for σ remained consistent. In particular, the TOP and $BOTTOM$ conditions, newly introduced in this experiment, exhibited similarly low R^2 values for σ, comparable to the $SAME$ condition. This suggests that most participants exhibited similar variability in their input timing under these conditions and that only distractors approaching from the $OPPOSITE$ direction induced greater variance in σ. Moreover, with four distinct distractor directions, our model also achieved strong performance in the $INTEGRATED$ condition for ER ($R^2 = 0.94$). These results suggest that the same model structure can estimate ER well under task conditions that were not included in the initial experiment, while σ remains more sensitive to departure direction.

5.4.2 Results of Game-based Scenario. In total, we collected 1,944 data points, and we found 100 outliers (5.14%) in this experiment. The observed ER was 31.55(0.24)%. To see the normality, we ran the KS test for each condition per participant. As a result, 85% of conditions (i.e., 139/162) formed a Gaussian distribution. We fit our model using current experimental data and obtained the following result as displayed in Figure 7(h).

$$\begin{cases} \mu = 0.319 - 0.159DD_t - 2.285DW_t^{**} \\ \quad + 3.419(DD_t \times DW_t)^{*} \\ \sigma = 0.140^{**} - 0.061DD_t^{*} \end{cases} \tag{13}$$

The last row in Table 3 presents the overall results for the game-based scenario. Our model demonstrated strong fitting performance for μ and ER despite the increased visual complexity of the interface. In particular, for predicting μ, the model achieved the highest accuracy with $R^2 = 0.96$. It outperformed the prediction of σ ($R^2 = 0.46$).

Table 3: Model fitting result for *DP* with nine data points. All metrics are from in-sample goodness-of-fit for user study 2.

Condition	*DP*	Selection Mean (μ)				Selection Std. (σ)				Error Rate	
		R^2	*MAE*	*AIC*	*BIC*	R^2	*MAE*	*AIC*	*BIC*	R^2	*MAE*(%)
Novel distractors	*SAME*	0.91	0.017	-37.14	-36.35	0.05	0.004	-65.65	-65.26	0.94	4.77
	OPPOSITE	0.91	0.030	-26.80	-26.01	0.91	0.002	-72.61	-72.22	0.95	6.79
	TOP	0.92	0.024	-31.01	-30.22	0.25	0.004	-65.70	-65.30	0.92	8.26
	BOTTOM	0.92	0.030	-27.31	-26.52	0.08	0.005	-61.25	-60.85	0.86	7.70
	INTEGRATED	0.91	0.020	-30.03	-29.24	0.72	0.002	-74.18	-73.78	0.94	6.32
Game-based	*SAME*	0.96	0.004	-58.87	-58.08	0.46	0.008	-54.37	-53.98	0.87	7.92

This trend is consistent with the findings from user study 1 (see Table 2). However, for σ, we observed a contrasting pattern compared to user study 1. Despite using the *SAME* direction condition in the current experiment, the model exhibited a relatively strong fit for σ. This result suggests that the complexity of the visual interface may have influenced the timing of user inputs. This led to a higher variance in between σ values (M = 0.0641, SD = 0.0137, and CV = 0.21) than observed in the simpler setup of user study 1. This result is also different from the novel distractor experiment (user study 2), which has relatively simple visual encoding. These results suggest that the same model structure can characterize user behavior in a visually more complex scenario, although the prediction of σ was weaker than that of μ. Furthermore, the model predicted *ER* in this novel and uncontrolled environment with relatively high performance (R^2 = 0.87), supporting its applicability to similar timing-based target selection scenarios.

6 General Discussion

6.1 Ablation Study for Model Fitting

6.1.1 Model Fitting with Whole Data Points. For modeling, we first looked at the fitting results with nine data points according to *DP*. While the model exhibited relatively high performance for μ and *ER*, we also sought to examine the fitting results of all individual data points corresponding to each *DP* for user study 1 (18 data points in total). We obtained fitting results, as shown in Figure 6 (d, i), for *HD* ($\mu : R^2 = 0.70, MAE = 0.015, AIC = -84.44, BIC = -80.87$, $\sigma : R^2 = 0.15, MAE = 0.009, AIC = -105.87, BIC = -104.09$, and $ER : R^2 = 0.89, MAE = 6.71\%$) and *LD* ($\mu : R^2 = 0.83, MAE = 0.021, AIC = -73.66, BIC = -70.10$, $\sigma : R^2 = 0.18, MAE = 0.011, AIC = -95.60, BIC = -93.82$, and $ER : R^2 = 0.85, MAE = 8.32\%$) Naturally, due to performance differences by *DP*, the data points were scattered; however, the model achieved reasonable performance for μ and *ER* compared to fitting *DP* separately in the *HD* and *LD* conditions. In the generalization scenario, we also examined the model with 36 data points ($DD_t \times DW_t \times DP$), which represent each condition (see Figure 7 (f)). The model showed reasonable performance for μ and *ER* (μ: R^2 = 0.86, MAE = 0.031; ER: R^2 = 0.85, MAE = 8.36%), but the fit for σ was weak (R^2 = 0.10). This result suggests that collapsing across *DP* can obscure direction-dependent variability in input timing. Therefore, *DP* should be explicitly considered when the goal is to model σ.

6.1.2 DP as an Independent Variable. While we only used numerical task parameters from the distractor (i.e., DD_t and DW_t), categorical variables could also be included in the linear regression by using a dummy-variable approach through one-hot encoding. As noted earlier, directly including categorical variables such as *DP* in this way would substantially increase dimensionality (e.g., linearly increased predictor) and complicate interpretation. Nevertheless, this approach may provide valuable insights when analyzing categorical effects. Specifically, for user study 1, *DP* and interaction term ($DD_t \times DP$) showed significant differences with a large effect size on both μ and σ. Therefore, we ran linear regressions and found strong fitting results. For *HD*, μ was well-predicted ($R^2 = 0.87, MAE = 0.009, AIC = -95.71, BIC = -91.36$) as well as σ ($R^2 = 0.78, MAE = 0.004, AIC = -126.49, BIC = -122.92$). The fitting results for *ER* also resulted in high performance ($R^2 = 0.97, MAE = 4.34\%$). Additionally, for *LD*, three DVs were well-estimated as follows: $\mu : R^2 = 0.91, MAE = 0.014, AIC = -80.61, BIC = -75.27$, $\sigma : R^2 = 0.84, MAE = 0.005, AIC = -121.96, BIC = -118.40$, and $ER : R^2 = 0.93, MAE = 5.77\%$. Compared to total results fit without consideration of *DP* as an IV (see Figure 6 (d, i)), using *DP* as an IV revealed effective performance (see Figure 6 (e, j)). While the model complexity might be increased due to appended IVs, model efficiency was improved in μ and σ prediction (ΔAIC and ΔBIC > 5), respectively. For novel distractors' direction, we also fit linear regression using *DP* as an IV (N=36). The fitting results are as follows: $\mu : R^2 = 0.91, MAE = 0.002, AIC = -130.21, BIC = -114.37$, $\sigma : R^2 = 0.85, MAE = 0.004, AIC = -261.85, BIC = -249.18$, and $ER : R^2 = 0.90, MAE = 6.84\%$. In this context, the prediction performances were effective and efficient (high R^2 and small *AIC*/*BIC*). In particular, the predictive performance of σ has improved dramatically. As shown in Table 1, *DP* had a significant impact on user input timing. Therefore, *DP* should be considered as an IV when modeling input variability.

6.2 Untested Scenarios and Applicability

We limited our research scope in Section 2.1 since the distractors' factors are dependent on the target factors (overlapping or not in the selectable area). As an initial step in understanding distractor effects on temporal target selection, we primarily focused on simple factors (DD_t, DW_t, and *DP*). However, this research field has the potential to extend to remarkably complex settings by considering various aspects of the distractor and cursor as follows: (1) differences in visual size and speed (e.g., large and fast vs. small and slow) while occupying the target region for the same temporal window, and their impact on *ER*; (2) conditions where the target and distractor start from the same direction but at different initial distances, potentially altering participants' ability to judge relative speeds; and (3) cursor movement parameters, such as cursor speed, cursor duration, and whether users can correct the cursor trajectory after triggering the input.

Based on our current results, we can speculate on how these untested scenarios might influence user behavior and performance. (1) In terms of visual size and speed, our findings showed that larger DW_t shifted μ earlier in time, particularly when $D_t > DD_t$, and that distractors arriving closer to the target's timing generally increased *ER*. We therefore expect that a large-and-fast distractor, even when occupying the target region for the same temporal window as a small-and-slow one, would likely amplify early-trigger strategies and result in higher *ER*. However, the present study did not independently manipulate visual size and physical speed while holding the temporal window constant. Future work should therefore examine whether visual size or physical speed produces additional effects beyond DD_t and DW_t. (2) In the case where the target and distractor start from the same direction but at different initial distances, the significant *DP* effect in our data suggests that the starting position changes perceptual load and timing strategies. When the distractor's initial distance is longer than the target, users may have more time to perceive the relative speed difference before overlap, potentially reducing early input bias. Conversely, when the distractor's initial distance is shorter than the target, the reduced time for speed judgment may strengthen early-trigger strategies or increase *ER*. (3) Cursor speed may also affect temporal target selection. In our study, the cursor duration (R_t) was fixed to isolate the effects of distractor parameters. However, if the cursor moves more slowly, users may need to predict the future interception between the cursor, target, and distractor over a longer time horizon. This could make the timing decision more difficult even when D_t, W_t, DD_t, and DW_t remain the same.

These considerations also clarify the applicability of our model. The current model is most relevant to timing-based game scenarios in which users trigger an action after observing moving entities, and the triggered cursor or projectile follows a fixed duration and trajectory. Examples include shooting, jumping, and obstacle-avoidance mechanics where the main difficulty comes from estimating when the target and distractor occupy the selectable area. In contrast, the model is less directly applicable to games that allow continuous control or post-trigger correction, such as steering a projectile after launch, dragging a cursor toward a moving target, or adjusting cursor speed during movement. For such cases, additional parameters, including cursor speed, acceleration, post-trigger controllability, visual size, and initial distance, should be considered.

6.3 Contribution to HCI

Our study shows that a predictive model incorporating DD_t, DW_t, and *DP* can capture user behavior and *ER* across varied distractor conditions under fixed target-timing settings. This extends the applicability of performance modeling beyond single-target or non-distractor temporal selection setups to more dynamic interaction contexts in which users must time their input while avoiding moving distractors. Our work therefore broadens the design space for temporal interaction tasks by showing that distractor timing, duration, and departure direction can be treated as design parameters that systematically affect user behavior and performance.

More specifically, our findings provide concrete takeaways for designers of temporal target selection. First, DD_t determines when the distractor interferes with the target's selectable time window, and our results show that this temporal relationship can shift users' input timing. Second, DW_t changes how long the distractor occupies the selectable area, thereby changing the effective temporal opportunity for successful selection. Third, *DP* is not merely a visual-layout factor; it can affect input variability, suggesting that the direction from which a distractor approaches should also be considered when designing task difficulty. For example, in timing-based interactions such as shooting, jumping, or obstacle-avoidance tasks, designers can manipulate these distractor parameters to make a selection event more forgiving or more demanding [10, 40].

The predictive accuracy achieved by our model can help designers and developers estimate performance outcomes for untested distractor configurations, including different movement timings, durations, and directions. Exhaustive empirical testing would require testing many combinations of DD_t, DW_t, and *DP* with users to identify distractor configurations that produce a desired level of task difficulty. Rather than replacing empirical user testing, the model can support early-stage parameter screening [15, 18]. For example, after testing a subset of distractor parameters, designers could use the model to estimate which untested configurations are likely to produce a desired range of *ER* before conducting a full user study. In this context, *ER* can serve as a practical proxy for task difficulty: configurations with lower predicted *ER* can be used for more forgiving scenarios, whereas configurations with higher predicted *ER* can be used for more demanding scenarios. This capability can inform difficulty balancing in distractor-rich temporal interaction scenarios, while remaining within the scope of fixed target-timing conditions.

6.4 Limitations

While our findings offer valuable insights into temporal target selection under distractor conditions, several limitations should be noted. First, our participant pool was young, computer-savvy students, which may limit the generalizability of the results to broader populations. In our study, participants were given unlimited time to observe the motion before making a selection. However, such conditions are unlikely to reflect real-world interactive game scenarios. If time constraints or penalties discussed in [30, 31] are implemented, the behavioral differences observed between conditions would likely become even more pronounced. In designing the experiments, we limited the range of the distractor's temporal parameters (DD_t, DW_t, and DR_t) based on the operational definition that interference is considered meaningful only when the distractor overlaps with the selectable area. However, it is important to note that even when no direct overlap occurs within the selectable window, the mere visual presence of the distractor may still affect user behavior and performance. Future studies could investigate such effects to further refine our understanding of temporal interference. Unlike prior work that manipulated cursor speed in the temporal target selection task [39], we maintained a fixed cursor duration. This decision was made to more clearly observe the effects of distractor parameters, but future work may benefit from incorporating the cursor duration as an additional variable. We used a simple linear regression model, chosen for interpretability and basic condition testing. More sophisticated approaches, such as cue integration or Bayesian methods, may capture additional structure and should be explored in future work. We need to add additional behavior metrics, such as target movement observation time or penalty when participants hit the distractor. In this context, we might find novel behavior differences.

7 Conclusion

Compared to spatial distractors, temporal distractors remain relatively underexplored. In temporal target selection, distractors may interfere with users' estimation of the timing of cursor-target selection. This paper examined the effect of distractors on temporal target selection. We defined key distractor parameters and conducted a controlled user study with two main conditions (*HD* and *LD*). Results showed that these parameters influenced user behavior and performance. Based on the findings, we developed a predictive model using empirical data from user study 1. Our model captured selection mean and *ER* well across several distractor conditions, while the prediction of selection variability (σ) was more sensitive to *DP*. Specifically, models that considered *DP* showed improved fitting results for σ, indicating that departure direction is important for modeling input variability. Additionally, two uncontrolled user studies showed that the same model structure could estimate *ER* in additional scenarios. Overall, our findings address gaps not previously explored in the literature and offer important insights into user behavior and performance in temporal target selection tasks involving distractors. We hope that our results will assist interactive game designers, practitioners, and researchers in evaluating and refining their designs — even for parameters that have not yet been empirically tested. Moreover, we view this work as a starting point for research on temporal distractors and anticipate that it will inspire further investigations in this area.

Acknowledgment

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT)(RS-2026-25481274).

References

[1] Nikola Banovic, Tovi Grossman, and George Fitzmaurice. 2013. The effect of time-based cost of error in target-directed pointing tasks. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 1373–1382.

[2] Xiaojun Bi and Shumin Zhai. 2016. Predicting finger-touch accuracy based on the dual Gaussian distribution model. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*. 313–319.

[3] Renaud Blanch and Michael Ortega. 2011. Benchmarking pointing techniques with distractors: adding a density factor to Fitts' pointing paradigm. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 1629–1638.

[4] Kelly Caine. 2016. Local standards for sample size at CHI. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 981–992.

[5] Jacob Cohen. 2013. *Statistical power analysis for the behavioral sciences*. routledge.

[6] Zahra Emami and Tom Chau. 2020. The effects of visual distractors on cognitive load in a motor imagery brain-computer interface. *Behavioural brain research* 378 (2020), 112240.

[7] Madeleine Frister. 2024. *Perceptual Distraction and its Effects on Difficulty and User Experience in Digital Games*. Ph. D. Dissertation. University of York.

[8] Jin Huang and Byungjoo Lee. 2019. Modeling error rates in spatiotemporal moving target selection. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–6.

[9] Jin Huang, Feng Tian, Xiangmin Fan, Huawei Tu, Hao Zhang, Xiaolan Peng, and Hongan Wang. 2020. Modeling the endpoint uncertainty in crossing-based moving target selection. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–12.

[10] Robin Hunicke. 2005. The case for dynamic difficulty adjustment in games. In *Proceedings of the 2005 ACM SIGCHI International Conference on Advances in computer entertainment technology*. 429–433.

[11] Nobuhito Kasahara, Yosuke Oba, Shota Yamanaka, Anil Ufuk Batmaz, Wolfgang Stuerzlinger, and Homei Miyashita. 2024. Better Definition and Calculation of Throughput and Effective Parameters for Steering to Account for Subjective Speed-accuracy Tradeoffs. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–18.

[12] Nobuhito Kasahara, Yosuke Oba, Shota Yamanaka, Wolfgang Stuerzlinger, and Homei Miyashita. 2023. Throughput and Effective Parameters in Crossing. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–9.

[13] Hyunchul Kim, Kasper Hornbæk, and Byungjoo Lee. 2022. Quantifying Proactive and Reactive Button Input. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–18.

[14] Sunjun Kim, Byungjoo Lee, and Antti Oulasvirta. 2018. Impact activation improves rapid button pressing. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–8.

[15] Byungjoo Lee, Sunjun Kim, Antti Oulasvirta, Jong-In Lee, and Eunji Park. 2018. Moving target selection: A cue integration model. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–12.

[16] Byungjoo Lee and Antti Oulasvirta. 2016. Modelling error rates in temporal pointing. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 1857–1868.

[17] Dawon Lee, Sunjun Kim, Junyong Noh, and Byungjoo Lee. 2024. User Performance in Consecutive Temporal Pointing: An Exploratory Study. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–15.

[18] Injung Lee, Hyunchul Kim, and Byungjoo Lee. 2021. Automated playtesting with a cognitive model of sensorimotor coordination. In *Proceedings of the 29th ACM International Conference on Multimedia*. 4920–4929.

[19] Injung Lee, Sunjun Kim, and Byungjoo Lee. 2019. Geometrically compensating effect of end-to-end latency in moving-target selection games. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–12.

[20] I Scott MacKenzie. 2018. Fitts' law. *The wiley handbook of human computer interaction* 1 (2018), 347–370.

[21] Antti Oulasvirta, Per Ola Kristensson, Xiaojun Bi, and Andrew Howes. 2018. *Computational interaction*. Oxford University Press.

[22] Eunji Park and Byungjoo Lee. 2020. An intermittent click planning model. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13.

[23] Andries F Sanders and Andries Sanders. 2013. *Elements of human performance: Reaction processes and attention in human skill*. Psychology Press.

[24] Rongkai Shi, Yushi Wei, Yue Li, Lingyun Yu, and Hai-Ning Liang. 2023. Expanding Targets in Virtual Reality Environments: A Fitts' Law Study. In *2023 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*. IEEE, 615–618.

[25] Huawei Tu, Jin Huang, Hai-Ning Liang, Richard Skarbez, Feng Tian, and Henry Been-Lirn Duh. 2021. Distractor effects on crossing-based interaction. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–13.

[26] Yushi Wei, Rongkai Shi, Difeng Yu, Yihong Wang, Yue Li, Lingyun Yu, and Hai-Ning Liang. 2023. Predicting gaze-based target selection in augmented reality headsets based on eye and head endpoint distributions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–14.

[27] Alan Traviss Welford. 1968. Fundamentals of skill. (1968).

[28] Jacob O Wobbrock, Edward Cutrell, Susumu Harada, and I Scott MacKenzie. 2008. An error model for pointing based on Fitts' law. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1613–1622.

[29] Jacob O Wobbrock, Alex Jansen, and Kristen Shinohara. 2011. Modeling and predicting pointing errors in two dimensions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 1653–1656.

[30] Shota Yamanaka. 2018. Effect of gaps with penal distractors imposing time penalty in touch-pointing tasks. In *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services*. 1–11.

[31] Shota Yamanaka. 2018. Risk effects of surrounding distractors imposing time penalty in touch-pointing tasks. In *Proceedings of the 2018 ACM International Conference on Interactive Surfaces and Spaces*. 129–135.

[32] Shota Yamanaka, Taiki Kinoshita, Yosuke Oba, Ryuto Tomihari, and Homei Miyashita. 2023. Varying subjective speed-accuracy biases to evaluate the generalizability of experimental conclusions on pointing-facilitation techniques. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–13.

[33] Shota Yamanaka, Hiroaki Shimono, and Homei Miyashita. 2019. Towards more practical spacing for smartphone touch GUI objects accompanied by distractors. In *Proceedings of the 2019 ACM International Conference on Interactive Surfaces and Spaces*. 157–169.

[34] Shota Yamanaka and Wolfgang Stuerzlinger. 2019. Modeling fully and partially constrained lasso movements in a grid of icons. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems.* 1–12.

[35] Shota Yamanaka and Wolfgang Stuerzlinger. 2024. The Effect of Latency on Movement Time in Path-steering. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems.* 1–19.

[36] Shota Yamanaka, Wolfgang Stuerzlinger, and Homei Miyashita. 2017. Steering through sequential linear path segments. In *Proceedings of the 2017 CHI conference on human factors in computing systems.* 232–243.

[37] Shota Yamanaka, Wolfgang Stuerzlinger, and Homei Miyashita. 2018. Steering through successive objects. In *Proceedings of the 2018 CHI conference on human factors in computing systems.* 1–13.

[38] Difeng Yu, Hai-Ning Liang, Xueshi Lu, Kaixuan Fan, and Barrett Ens. 2019. Modeling endpoint distribution of pointing selection tasks in virtual reality environments. *ACM Transactions on Graphics (TOG)* 38, 6 (2019), 1–13.

[39] Difeng Yu, Brandon Victor Syiem, Andrew Irlitti, Tilman Dingler, Eduardo Velloso, and Jorge Goncalves. 2023. Modeling Temporal Target Selection: A Perspective from Its Spatial Correspondence. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems.* 1–14.

[40] Mohammad Zohaib. 2018. Dynamic difficulty adjustment (DDA) in computer games: A review. *Advances in Human-Computer Interaction* 2018, 1 (2018), 5681652.

A Error Rate Prediction with Existing Models

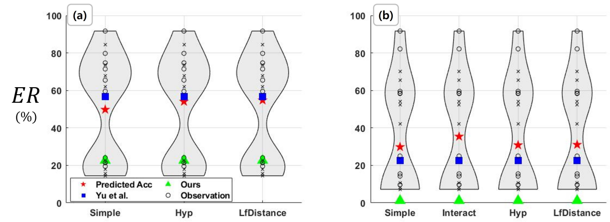

Figure 5: Illustration of results of prediction models. (a): Results of the *HD*. (b): Results of the *LD*. Blue square, red star, and green triangle represent *ER*s from [39]'s user study, the prediction results of each model, and our baseline, respectively. Each black one denotes *ER* from each distractor condition. X mark and circle stand for *SAME* and *OPPOSITE*, respectively.

Based on both pre-established *ER* prediction models on temporal target selection and open-source data from [39], we validated how well existing models generalize to scenarios with distractors. To this end, we employed four models as follows: *Simple*, *Interact*, *Hyp*, and *LfDistance* model (see Equations (14) to (17), respectively). While *Simple*, *Interact*, and *Hyp* are based on linear regression approaches, *LfDistance* employs a non-linear model. These models were originally fit to the empirical data collected in the experiment scenario from [39] corresponding to our baseline conditions. The predictions of the model fitting, in the *HD* ($D_t = 0.75; W_t = 0.125, R_t = 0.2$), are $\mu = 0.0908; \sigma = 0.0875$, $\mu = 0.0758; \sigma = 0.1012$, and $\mu = 0.0396; \sigma = 0.1012$ from *Simple*, *Hyp*, and *LfDistance* model, respectively. Since *Interact* produced identical results to *Simple*, we only used the *Simple* model. For reference, empirical data in the *HD* of [39] is $\mu = 0.0373; \sigma = 0.1026$ and $ER = 56.7\%$. In the *LD* ($D_t = 1.0; W_t = 0.25, R_t = 0.2$), empirical data of [39] is $\mu = 0.0872; \sigma = 0.1359$ and $ER = 22.7\%$. *Simple*, *Interact*, *Hyp*, and *LfDistance* models predict selection distribution as follows: $\mu = 0.0673; \sigma = 0.1040$, $\mu = 0.0460; \sigma = 0.1040$, $\mu = 0.0873; \sigma = 0.1165$, and $\mu = 0.0855; \sigma = 0.1165$, respectively. Notably, the *ER*s of our baselines (22.6% and 1.2%) are significantly lower than [39] (56.7% and 22.7%) for both conditions. We infer that these differences may stem from the experimental context that included distractor trials, which may have encouraged participants to adopt more careful timing strategies even in the baseline conditions.

Afterward, we compared the predicted performance of each model, in terms of *ER*, with our empirical observations using the probability density functions defined in Equations (18) to (20), as illustrated in Figure 5. As a result, none of the models could cover the wide range of *ER* for distractor conditions. In other words, for both *HD* and *LD* cases, the presence of the distractor alone produced a wide range of performance differences under identical baseline conditions. In conclusion, our findings reveal that temporal target selection with distractors represents a fundamentally distinct interaction scenario that existing state-of-the-art models fail to capture accurately. The inability of current models to effectively predict performance in our experimental conditions underscores the profound impact of distractor-related variables (DD_t, DW_t, and DP) on temporal target selection behavior. This study not only highlights the limitations of existing models but also presents opportunities for developing more sophisticated human behavior models that can effectively incorporate these additional temporal and spatial factors. Such refinements would advance our understanding of human performance in more complex, real-world temporal selection tasks where distractors are common.

B Selection Error Rate Prediction

To see if the performance of the task of temporal target selection with the distractor can be predicted successfully, we employed four models from [39] as follows:

$$Simple = \begin{cases} \mu = 0.166 - 0.094D_t + 0.227R_t \\ \sigma = 0.038 + 0.066D_t \end{cases} \tag{14}$$

$$Interact = \begin{cases} \mu = -0.076 - 0.161D_t + 1.505R_t - 1.704D_t \times R_t \\ \sigma = 0.038 + 0.066D_t \end{cases} \tag{15}$$

$$Hyp = \begin{cases} \mu = 0.166 - 0.194(D_t - R_t) + 0.480W_t + 0.033R_t \\ \sigma = -0.002 + 0.070(D_t - R_t) - 0.017W_t + 0.333R_t \end{cases} \tag{16}$$

$$LfDistance = \begin{cases} \mu = -0.02 - \frac{2.198}{1+e^{8.896(D_t - R_t)}} + 0.484W_t - 0.080R_t \\ \sigma = -0.002 + 0.070(D_t - R_t) - 0.017W_t + 0.333R_t \end{cases} \tag{17}$$

Based on the outputs of these models, we can predict selection ER based on previous works [2, 39].

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(t-\mu)^2}{2\sigma^2}} \tag{18}$$

$$E = 1 - \int_0^{W_t} f(t)\, dt = 1 - \frac{1}{2}[erf(\frac{W_t - \mu}{\sigma\sqrt{2}}) + erf(\frac{\mu}{\sigma\sqrt{2}})] \tag{19}$$

where $erf(z)$ is the error function defined as:

$$erf(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-t^2}\, dt \tag{20}$$

Additionally, we modified the above equations to employ in $D_t < DD_t$.

$$E = 1 - \int_0^{DD_t - D_t} f(t)\, dt = 1 - \frac{1}{2}[erf(\frac{DD_t - D_t - \mu}{\sigma\sqrt{2}}) + erf(\frac{\mu}{\sigma\sqrt{2}})] \tag{21}$$

For $D_t > DD_t$, we used the following equation.

$$E = 1 - \int_0^{D_t + W_t - DD_t - DW_t - (R_t - DR_t)} f(t)\, dt \tag{22}$$

$$= 1 - \frac{1}{2}\left[\text{erf}\left(\frac{D_t + W_t - DD_t - DW_t - (R_t - DR_t) - \mu}{\sigma\sqrt{2}}\right)\right. \tag{23}$$

$$\left. + \text{erf}\left(\frac{\mu}{\sigma\sqrt{2}}\right)\right] \tag{24}$$

Other processes are equivalent to [39].

C Visualization of Correlation Plots in Controlled User Study

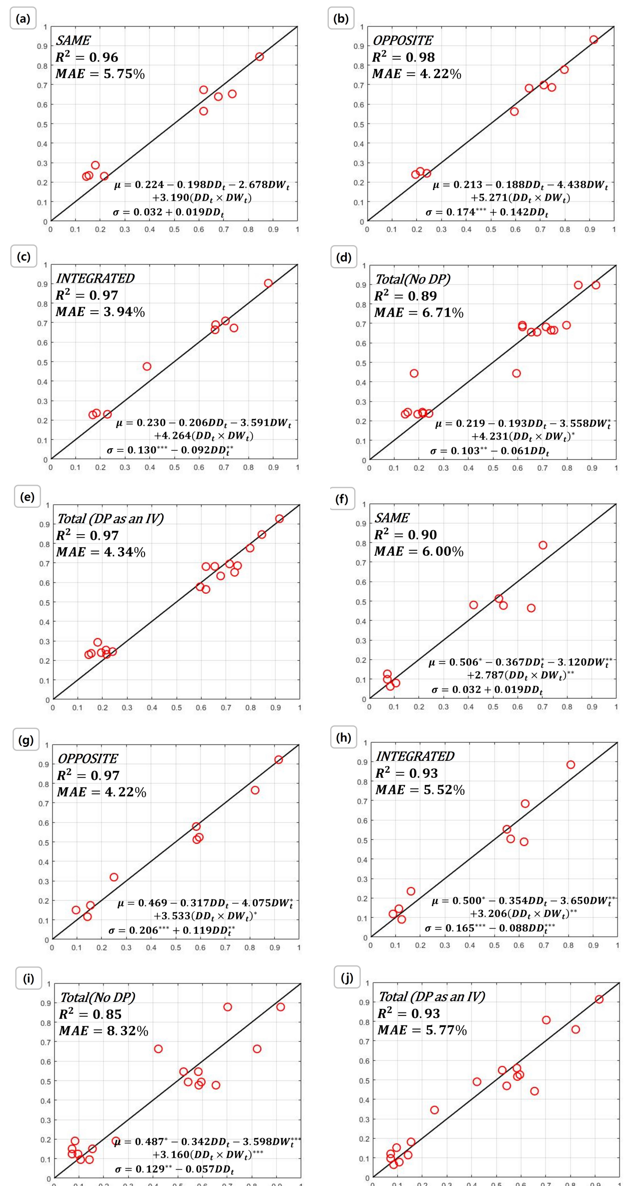

Figure 6: In-sample goodness-of-fit (correlation) plots between observations and predictions for user study 1. Top (a-e) and bottom (f-j) stand for HD and LD. The notation (i.e., $*$) for each parameter in models, including the intercept, means the statistical significance ($^* = p < .05$, $^{**} = p < .01$, and $^{***} = p < .001$).

D Visualization of Correlation Plots in Uncontrolled User Study

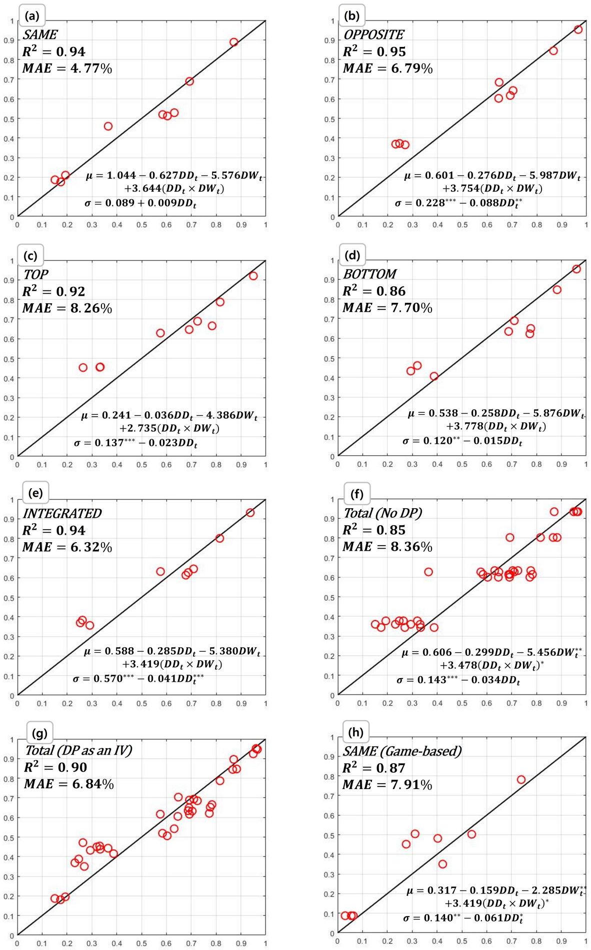

Figure 7: In-sample goodness-of-fit (correlation) plots between observations and predictions for user study 2. (a-f) and (h) stand for novel distractor and game-based scenarios, respectively. The notation (i.e., $*$) for each parameter in models, including the intercept, means the statistical significance ($^{*} = p < .05$, $^{**} = p < .01$, and $^{***} = p < .001$).

Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009