A Model for Pointing at Targets with Different Clickable and Visual Widths and with Distractors

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ABSTRACT

In this study, we extend Fitts' law to enable it to predict the movement time of pointing operations in interfaces, such as those in navigation bars whose items have different clickable and visual widths and intervals between a target and distractors. For this, we conduct two experiments to investigate the effects of distractors on pointing operations and how increasing the interval size changes user performance. We find that the movement time is significantly affected by the clickable width and intervals whereas it is only slightly affected by the visual width. Based on the results, we construct a time prediction model for considering the differences between clickable and visual widths and the intervals between a target and distractors. Our model shows a good fit for not only the data of our two experiments but also for those of three previous studies.

CCS CONCEPTS

• **Human-centered computing** → *HCI theory, concepts and models.*

KEYWORDS

Difference between clickable and visual widths, distractor, pointing, Fitts' law, GUIs

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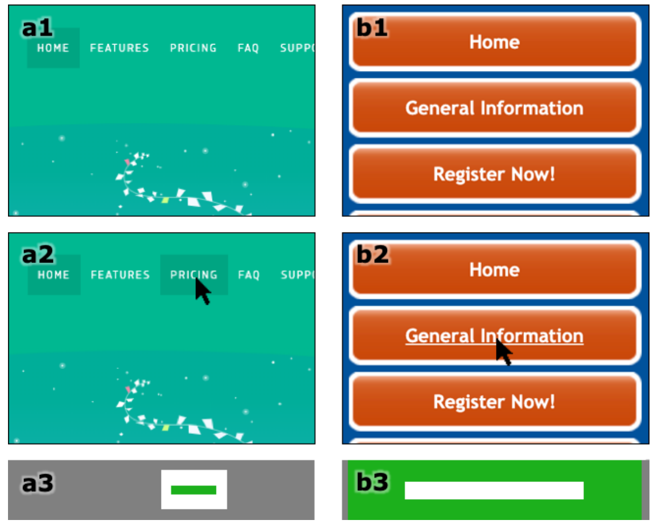

Figure 1: Two navigation-bar examples. Clickable width (white) is (a) larger or (b) smaller than the visual width (green). In both navigation bars, the target is surrounded by distractors. In (b), there are intervals between the target and distractors.

1 INTRODUCTION

Pointing is a fundamental user operation supported by graphical user interfaces (GUIs). By applying this process, users can move a cursor to click on a desired object (i.e., *target*) on the screen. In Figure 1, we provide examples of pointing operations, including the clicking of target on navigation bars. In Figure 1a[1], users want to go to another page, so they click an item ("PRICING") in the navigation bar (a1). At this time, the users may aim at the item's text because it is unclear where the item is clickable (they may believe that the text at least is clickable). However, when the user's cursor enters the clickable area, the area is highlighted with a dark color (a2) so that the user realizes that the clickable area is larger than the item's text (a3). Thus, to accomplish his or her navigation goal, the user can click not only the item's text, but also on its surrounding area. In this paper, we define this area as the *clickable width*, and the area displayed on the screen is the *visual width*. In this situation, the clickable width is larger than the visual width (item's text). In contrast, Figure 1b[2], which is from [25], shows a situation where the clickable width is smaller than the visual width. The user can aim at the entire orange button but can only click the item's text, "General Information."

In GUIs, the clickable and visual widths are often different. Of course, situations in which the clickable width equals the visual width exist. Additionally, the target, as shown in Figure 1, is sandwiched by *distractors* that the user does not want to click. The distractors have similar appearances, clickable widths, and visual widths as the target. Thus, the user must point at the target successfully while avoiding the distractors. Moreover, intervals between the target and its distractors do not exist (Figure 1a) or do exist (Figure 1b).

[1] https://www.stillio.com/

[2] https://web.archive.org/web/20110308051632/http://www.asaging.org/aia11/

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Fitts' law can be used to predict movement time (MT) based on the width of (W) and the distance to (A) the target (Equation 1). As shown in Figure 1, the target has two widths: clickable and visual. However, it is undefined whether the W in Fitts' law indicates the clickable or visual width. Thus, the range in which Fitts' law is used is limited to situations in which the clickable and visual widths are equal. In this study, we extend Fitts' law to enable it to predict movement times, even when the clickable and visual widths are different. Furthermore, our model can consider the intervals between the target and its distractors. Hence, navigation bars, such those in Figure 1, can be adjusted on the basis of a quantitative model. To build a time prediction model that considers such factors, we conduct two experiments to investigate how the presence or absence of distractors affects pointing operations (Figure 2b) and how the users' performance changes when the intervals between the target and distractors are enlarged (Figure 2c).

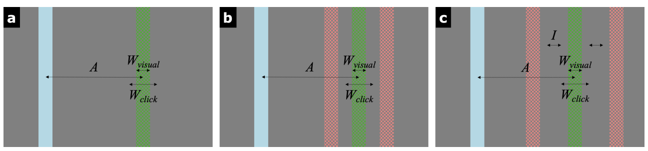

Figure 2: (a) Previous study's task [32, 33]. (b) Our Experiment 1 task. (c) Our Experiment 2 task. A is distance to the target, W_{click} is the clickable width, W_{visual} is the visual width, and I is the interval between the target and its distractors. In (a), participants must click the blue start area, then the green target. In (b) and (c), they must click the start area followed by the clickable width of target while avoiding red distractors.

In design guidelines (e.g., Apple, Google), the sizes of buttons, texts, and margins are strictly determined. That is, their GUI designers adjust the sizes of the components to reduce the movement time by a few milliseconds or improve the accuracy of pointing operations by a few percentage points. Thus, we believe that if our model can even marginally improve the prediction accuracy of the movement time, it will contribute to the success of GUI designers and their guidelines. For example, by using models that can consider more factors, GUI designers can make the components smaller without slowing user operations. Reducing the movement time by 100 ms may not appear to be significant. However, users perform pointing operations many times a day. Thus we believe that in the long run, reducing the movement time will have a considerable impact on the users' experience. In this study, we extend existing models for such purposes.

2 RELATED WORK

2.1 Pointing Model

Fitts' law [11, 19] is a pointing model for predicting MT and can be expressed as follows:

$$MT = a + b\log_2\left(\frac{2A}{W}\right) = a' + b\log_2\left(\frac{A}{W}\right) \tag{1}$$

where $a' = a + b\log_2 2$. Hereafter, all lowercase letters (excluding e) with/without a subscript indicate regression constants. We use the latter in Equation 1 as an equivalent version of the original Fitts' law. The logarithm term in Fitts' law is called the *index of difficulty* (ID). An increasing ID increases the predicted MT. There are many versions of Fitts' law [18, 23], and the Shannon formulation [27] appends +1 to the original Fitts' law. Equation 2, which reflects Shannon's formulation, is known to show a better fit.

$$MT = a + b\log_2\left(\frac{A}{W} + 1\right) \tag{2}$$

If two different input devices are compared, one would find that one device is faster but less accurate than the other. Thus, it is difficult to answer the question of which device performs better. In such cases, researchers have used the effective width, which can adjust the error rates of the input devices to render them the same [17, 28, 30]. This allows us to compare the two devices, assuming that they have the same accuracy. The effective width ($W_e = \sqrt{2\pi e}\sigma$) is calculated using the standard deviation (σ) of clicked endpoints, where W in ID is replaced with W_e, and the index of difficulty is ID_e (Equation 3).

$$ID_e = \log_2\left(\frac{A}{W_e} + 1\right) \tag{3}$$

Using the effective amplitude, A_e, instead of A in Equation 3, enables us to adjust the distance. However, the effect of A_e is smaller than that of W_e [42]. Thus, we use ID_e based only on W_e.

In traditional Fitts' tasks, the target has a certain width and practically infinite height (i.e., a 1D pointing task). However, in actual GUIs, targets have finite width and height (i.e., the target is often rectangular, providing a 2D pointing task). There are many 2D pointing models, and we provide one example (Equation 4) [16].

$$MT = a + b\log_2\left(\frac{A}{W}\right) + c\log_2\left(\frac{A}{H}\right) \tag{4}$$

where H is the height of the target. This model means that W and H independently affect MT. However, Accot and Zhai [1] later found the interaction for $W \times H$ on MT. Thus, the model is modified as follows:

$$MT = a + b\log_2\sqrt{\left(\frac{A}{W}\right) + \eta\left(\frac{A}{H}\right)} \tag{5}$$

where η is the free weight. In Equation 4, when c is smaller than b, Equation 4 can be approximated as Equation 5 [24].

Blanch et al. [7] defined the index of sparseness (IS, Equation 6) by using spaces with distractors (ρ, range [0, 1]). When $\rho = 1$, there is no space between the target and its distractors, and, when ρ is decreased, the space between the target and its distractors is increased. Additionally, a movement time that considers the space can be expressed using Equation 6. Increasing the space (decreasing ρ) means decreasing the movement time.

$$IS = \log_2\frac{1}{\rho},\ MT = a + bID - cIS \tag{6}$$

2.2 Difference between Clickable and Visual Sizes of Targets

Usuba et al. investigated the effect of the difference between the clickable and visual widths on mouse-pointing operations via two studies [32, 33][3]. In both, the movement times strongly depended on clickable width and, although the effect of visual width was not significant, increasing it decreased the movement time. Additionally, σ depended on the clickable width. Thus, the effective width shows a good fit [32]. However, as noted in previous studies [13, 36, 42], because only the nominal width is informative to GUI designers, the effective width should be used, such as when comparing the performance of input devices when participant pointing precisions vary. Thus, a model that does not use the effective width is needed to predict the movement time in a situation in which a difference between the clickable and visual widths exists. In their studies, Usuba et al. did not develop such a model. They also did not consider the effect of distractors (Figure 2a). Furthermore, in touch-pointing operations, they examined the effect of the difference between the clickable and visual widths [34].

Area-cursor techniques [14, 21, 26, 31, 35] expand the activation area, wherein a click event fires on a cursor. Expanding the activation area is equivalent to expanding the target size (i.e., expanding the clickable width). In the dock of macOS, the icons become larger as the cursor approaches. This is called *target expansion* [15, 22, 41]. In both area-cursor and target expansion techniques, the movement time depends on the final target size (i.e., the clickable width). However, in many area-cursor and target expansion techniques, the activation area and target size dynamically change. Thus, the situation in focus for this study, wherein the clickable and visual widths are statically different, has rarely been explored.

2.3 Effect of Distractors on Pointing Operations

Blanch et al. [7] investigated and modeled mouse-pointing operations with distractors (Equation 6). In touch-pointing operations, the effect of the spaces between the target and its distractors was also investigated [37–39], which revealed that small spaces negatively affected the error rate but did not strongly change task completion time. A similar tendency in the effect was confirmed via crowd-based experiments [39]. Especially for touch operations, *placeholder effects* [2, 8] have been detected. This effect means that a target that is farther away can be acquired more quickly when items are lined up horizontally. In summary, user performance during pointing operations depends on the size of the space between the target and its distractors and whether the distractors exist.

3 EXPERIMENT 1: DISTRACTOR EFFECTS

3.1 Apparatus

We used an Apple MacBook Pro laptop (Intel Core i5, 2.4 GHz, two cores, Intel Iris 1536 MB, 8-GB RAM, macOS Sierra). The display scaling resolution was 1,680 × 1,050 pixels (the actual size was 13.3 in, 286.47 × 179.04 mm, 0.17 mm/pixel resolution). We used an optical gaming mouse, Logitech G-PPD-002WL (3,200 dpi), as the input device. The mouse was connected to the laptop with a 1.80 m cable. A sufficiently large mouse pad (899 × 420 mm) was used. The full-screen experimental system was developed using JavaScript.

[3]Usuba et al. called the clickable width the "motor width." The terms are different but the meanings is the same.

3.2 Participants

Twelve paid volunteers participated in this study (five females and seven males; age: M = 21.83, SD = 1.14, all right-handed, none color-blind). Each participant received the equivalent of US$46 for their time.

3.3 Task

Participants clicked on the start area to begin their trial and aimed for the target as quickly and as accurately as possible (Figure 2b). At the beginning of each trial, a starting sound was played. Then, measurement began. When a cross-hair cursor entered the clickable width of the target or distractor, as with the example navigation bar (Figure 1a), the clickable width was highlighted in white (Figure 3)[4]. When the participants clicked within the clickable width of the target, a success sound was played. Otherwise, a failure sound was played, and the trial was flagged as an error. Following previous studies [12, 13], we asked the participants to avoid *clutching* (i.e., replacing the mouse on the mouse pad)[5]. In unavoidable cases of clutching, participants were instructed to push their right mouse button to reaccomplish their trial. Retrials caused by clutching were not regarded as errors.

In real-life situations, users understand which object is the target through the differences in its appearance (e.g., text). During the task, if the target and its distractors had the same color, it was possible that the participants did not judge which object was the target. Thus, we used different color schemes with the target and its distractors.

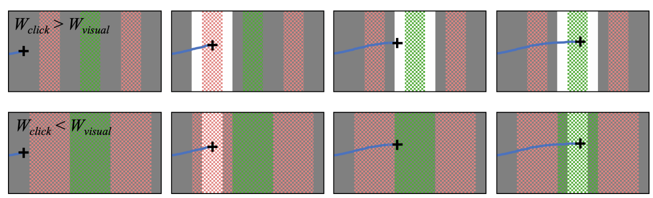

Figure 3: When the cross-hair cursor enters the clickable width of the target or its distractor, the clickable width is highlighted in white. Note that the blue trajectory is for explanation and did not appear in actual trials.

3.4 Design and Procedure

The distance A from the center of the start area to the center of the target was 600 or 800 pixels (102.31 or 136.41 mm, respectively). The clickable W_{click} and visual W_{visual} widths were 20, 40, 70, or 120 pixels (3.41, 6.82, 11.94, or 20.46 mm, respectively); the clickable width was larger than, equal to, or smaller than the visual width. To compare the effects of the distractors, we tested two conditions on

[4]Even if the visual width equals the clickable width, because the visual width is lit by highlighting the clickable width, the participants can perceive the highlight.
[5]Clutching can reduce the fitness of pointing models [12]. If we had allowed clutching and obtained poor regression fitness, it would have been unclear whether the results were caused by clutching or experimental conditions, such as the difference between the clickable and visual widths. Additionally, because we used a mouse having high dots-per-inch and avoided long-distance mouse travel (A), the participants comfortably completed their tasks without clutching. Thus, the task resembled real-life situations without clutching.

their existence. When *Distractor* = *True*, the red distractors existed in the task. When *Distractor* = *False*, there were none to see. We used the same values for A, W_{click} and W_{visual} as in previous studies [32, 33]. The values of clickable and visual widths of the start area equaled W_{visual}, because we wanted to prevent the participants from presuming the clickable width of the target before starting the trial. The clickable and visual widths of the target equaled those of the distractors. There was no margin between the larger of the clickable and visual widths (Figure 4).

One *set* consisted of $2A \times 4W_{click} \times 4W_{visual} = 32$ trials for a fixed *Distractor* condition. The orders of A, W_{click}, and W_{visual} were randomized in a set. By each *Distractor*, after an introductory practice set, each participant completed 10 sets to produce experimental data. The order of *Distractor* was balanced among the 12 participants. A total of 7,680 trials (i.e., $2Distractor \times 2A \times 4W_{click} \times 4W_{visual} \times$ 10 sets $\times$ 12 participants) was conducted, requiring approximately 20 min per participant.

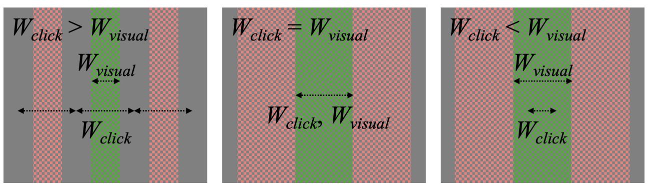

Figure 4: Arrangements of clickable and visual widths of target and distractors for three possible conditions.

3.5 Measurements

The dependent variables includes the dwell time, DT, which is the time from entering the target to clicking the target, excluding error trials. MT is the time from clicking the start area to clicking the target, excluding error trials. The standard deviation of the x-coordinate is SD_x, which includes the origin at the center of the target, including error trials, and error rate. Data processing followed procedures of prior studies [28, 30, 32, 33].

4 RESULTS

Among the 7,678 trials, two were outliers[6]), 143 errors occurred (1.86%). The error rate was lower than those of previous studies [21, 28, 30, 32]. According to the participants' comments after the experiment, they performed the pointing operation while watching the highlighted clickable widths. Thus, we believe that, owing to the highlight allowing them to operate more accurately, a lower error rate was observed. However, if true, it reflects the opposite effect of those found in previous studies [4, 5].

We analyzed the data by using repeated-measures analysis of variations with Bonferroni correction as the p-value adjustment method. In our graphs of the results, the error bars represent the standard error, and ***, **, and * indicate $p < 0.001$, $p < 0.01$, and $p < 0.05$, respectively. These conditions were the same for Experiment 2.

[6]When the clicked position was below $A/2$, the trial was regarded as an outlier following previous studies [6, 30, 32]. We did not use the criterion based on W, because this task had different clickable and visual widths.

4.1 Dwell Time

We observed the main effect for W_{click} ($F_{3,33} = 15.02, p < 0.001, \eta_p^2 = 0.58$), not *Distractor* ($F_{1,11} = 1.78, p = 0.21, \eta_p^2 = 0.14$), A ($F_{1,11} = 2.59, p = 0.14, \eta_p^2 = 0.19$) or W_{visual} ($F_{3,33} = 2.59, p = 0.07, \eta_p^2 = 0.19$). Figure 5 shows the results of the post hoc test. We also observed the interactions for $Distractor \times W_{click}$ ($F_{3,33} = 11.12, p < 0.001, \eta_p^2 = 0.50$), $A \times W_{visual}$ ($F_{3,33} = 4.00, p < 0.05, \eta_p^2 = 0.27$), $Distractor \times W_{click} \times W_{visual}$ ($F_{9,99} = 11.40, p < 0.001, \eta_p^2 = 0.51$, Figure 6), and $A \times W_{click} \times W_{visual}$ ($F_{9,99} = 2.18, p < 0.05, \eta_p^2 = 0.17$, Figure 6). Regarding $Distractor \times W_{click} \times W_{visual}$, when W_{visual} was small or when W_{click} was large, the difference between *Distractor* was significant. Regarding $A \times W_{click} \times W_{visual}$, decreasing W_{click} or increasing W_{visual} decreased DT.

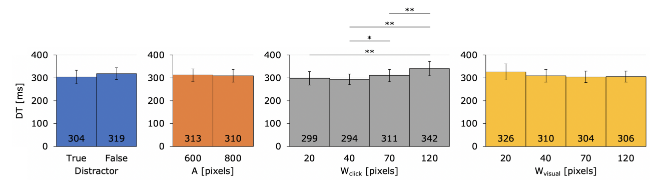

Figure 5: DT **vs.** *Distractor*, A, W_{click}, **and** W_{visual}.

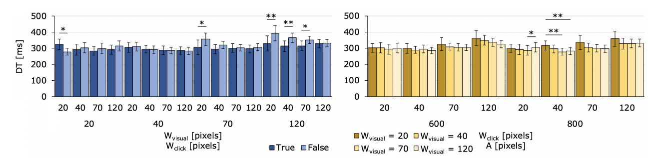

Figure 6: DT **for** $Distractor \times W_{click} \times W_{visual}$ **and** $A \times W_{click} \times W_{visual}$.

4.2 Movement Time

We observed the main effects for A ($F_{1,11} = 90.18, p < 0.001, \eta_p^2 = 0.89$) and W_{click} ($F_{3,33} = 326.65, p < 0.001, \eta_p^2 = 0.97$), not *Distractor* ($F_{1,11} = 1.14, p = 0.31, \eta_p^2 = 0.09$) or W_{visual} ($F_{3,33} = 2.49, p = 0.08, \eta_p^2 = 0.18$). Figure 7 shows the results of the post hoc test. We also observed the interactions for $Distractor \times W_{click}$ ($F_{3,33} = 6.01, p < 0.01, \eta_p^2 = 0.35$), $W_{click} \times W_{visual}$ ($F_{9,99} = 4.80, p < 0.001, \eta_p^2 = 0.30$), and $Distractor \times W_{click} \times W_{visual}$ ($F_{9,99} = 2.56, p < 0.05, \eta_p^2 = 0.19$). For $Distractor \times W_{click} \times W_{visual}$, the difference between *Distractor* was not significant, increasing W_{click} decreased MT, and increasing W_{visual} slightly decreased MT (Figure 8).

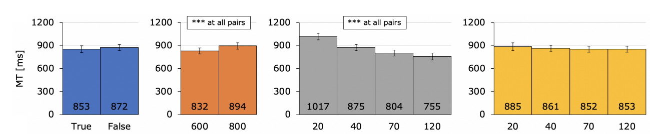

Figure 7: MT **vs.** *Distractor*, A, W_{click}, **and** W_{visual}.

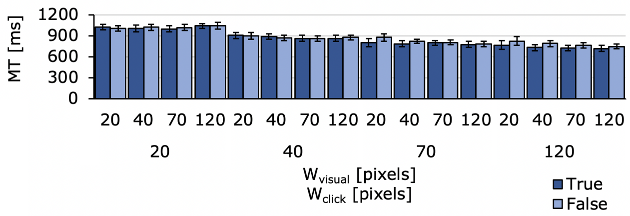

Figure 8: MT **vs.** $Distractor \times W_{click} \times W_{visual}$.

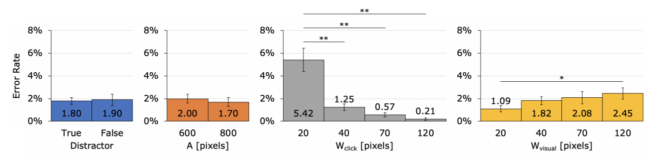

Figure 11: Error rate vs. $Distractor$, A, W_{click}, **and** W_{visual}.

4.3 Standard Deviation of x-coordinate

We observed the main effects for *Distractor* ($F_{1,11} = 31.49, p < 0.001, \eta_p^2 = 0.74$), W_{click} ($F_{3,33} = 95.20, p < 0.001, \eta_p^2 = 0.90$), and W_{visual} ($F_{3,33} = 2.98, p < 0.05, \eta_p^2 = 0.21$), not A ($F_{1,11} = 0.72, p = 0.41, \eta_p^2 = 0.06$). Figure 9 shows the results of the post hoc test. We also observed the interactions for $Distractor \times W_{click}$ ($F_{3,33} = 25.67, p < 0.001, \eta_p^2 = 0.70$), $Distractor \times W_{visual}$ ($F_{3,33} = 4.75, p < 0.01, \eta_p^2 = 0.30$), and $Distractor \times W_{click} \times W_{visual}$ ($F_{9,99} = 2.98, p < 0.01, \eta_p^2 = 0.21$). For $Distractor \times W_{click} \times W_{visual}$, when W_{click} was large, the difference between *Distractor* was significant (Figure 10).

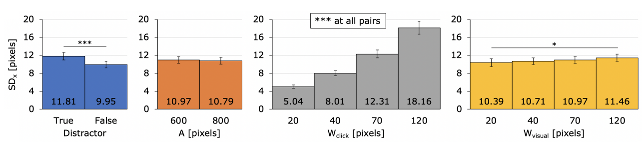

Figure 9: SD_x **vs.** $Distractor$, A, W_{click}, **and** W_{visual}.

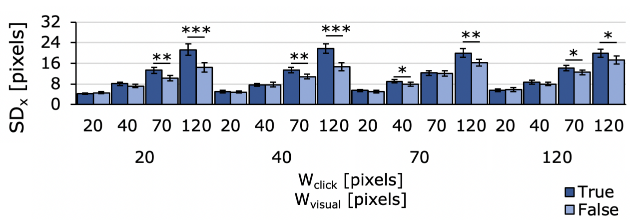

Figure 10: SD_x **vs.** $Distractor \times W_{click} \times W_{visual}$.

4.4 Error Rate

We observed the main effects for W_{click} ($F_{3,33} = 23.39, p < 0.001, \eta_p^2 = 0.68$) and W_{visual} ($F_{3,33} = 3.20, p < 0.05, \eta_p^2 = 0.23$), not *Distractor* ($F_{1,11} = 0.00, p = 0.95, \eta_p^2 = 0.00$) and A ($F_{1,11} = 0.24, p = 0.63, \eta_p^2 = 0.02$). Figure 11 shows the results of the post hoc test. No interactions were observed.

4.5 Model Fitting

Although there was no significant difference between *Distractor* conditions, we decided to verify the model fitness separated by each *Distractor*. Models did not include the variable, *Distractor*, because interfaces simulated by the task differed depending on their presence or absence. Additionally, we believe that it may be inconvenient for models to include *Distractor*, because, even if the absence of the distractors is predicted to decrease movement time, GUI designers cannot remove the distractors from a navigation bar, for example.

We found that movement time was affected significantly by clickable widths and slightly by visual widths (Figure 7). Thus, following previous studies [32, 33], we selected ID_m (Models #1 and #2 in Table 1) and ID_v (Models #3 and #4 in Table 1) as candidates. These models were built by replacing W in the original Fitts' law (Equations 1 and 2) with the clickable (W_{click}) or visual (W_{visual}) width. As shown in Table 1, the model fitness of the ID_m models when $Distractor = False$ was below the typical threshold ($R^2 < 0.900$) [30]. We also found that the visual width affected the spread of clicked positions and error rates (Figures 9 and 11). Thus, interfaces designed on the basis of ID_m (i.e., only considering the clickable width) can frustrate users when they perform pointing operations. Thus, we believe that the model should include the visual width.

When users perform operations on interfaces wherein clickable and visual widths are different, they can only aim for the visual width at first, see the clickable width by highlighting it, and operate a cursor on the basis of the clickable width. Based on the results that the interactions for $A \times W_{click}$ and $A \times W_{visual}$ were not observed and that increasing visual width slightly decreased movement times, visual width may be added to the model in a form similar to clickable width. Thus, our model is expressed as Model #5 in Table 1. With normal Fitts' tasks, clickable width equals visual width (i.e., $W_{click} = W_{visual}$). When $W_{click} = W_{visual}$ and letting $b' = b + c$, our model equals the original Fitts' law (Equation 1). Additionally, Model #5 in Table 1 can be converted to Model #7 in Table 1. According to Hoffmann et al. [24], if c is smaller than b, then approximation is possible. It should be noted that Model #7 in Table 1 was not derived to account for the weighted Euclidean distance of the target width and height, as proposed in a previous study [1]. We found that the effect of W_{visual} on movement time was smaller than that of W_{click} ($\eta_p^2 = 0.18$ vs. 0.97, respectively). Thus, we believe that c may also become small, enabling approximation. Model #7 in Table 1, when $W_{click} = W_{visual}$, letting $a' = a + b \log_2 \sqrt{(1 + c)}$, equals Equation 1. That is, our two models have consistency with the original Fitts' law.

In addition to these models, we verified their Shannon formulation versions (Models #6 and #8 in Table 1) where +1 was added to the logarithm term. It was revealed that +1 improved model fitness [18, 23, 24, 27, 28]. Thus, we added the +1 versions to the candidate models. Such a posteriori modification had been conducted previously [10].

Table 1: Model fitting by each *Distractor* ($N = 32$). All regression constants having 95% confidence intervals (CIs) [lower, upper].

	Model	Equation	*Distractor = True*					*Distractor = False*				
			a	b	c	adj. R^2	AIC	a	b	c	adj. R^2	AIC
#1	ID_{m1}	$MT = a + b\log_2\left(\frac{A}{W_{click}}\right)$	431 [394, 470]	112 [102, 122]		0.948	306	515 [461, 569]	95.0 [81.1, 109]		0.872	328
#2	ID_{m2}	$MT = a + b\log_2\left(\frac{A}{W_{click}} + 1\right)$	382 [341, 423]	121 [111, 131]		0.953	304	472 [414, 530]	103 [88.3, 17]		0.879	326
#3	ID_{v1}	$MT = a + b\log_2\left(\frac{A}{W_{visual}}\right)$	791 [622, 959]	16.6 [-26.6, 59.8]		0.021	401	794 [647, 941]	20.9 [-16.9, 58.7]		0.042	392
#4	ID_{v2}	$MT = a + b\log_2\left(\frac{A}{W_{visual}} + 1\right)$	783 [597, 969]	17.9 [-28.7, 64.5]		0.021	401	785 [622, 948]	22.6 [-18.2, 63.3]		0.042	392
#5	ID_{mv1} (segmented)	$MT = a + b\log_2\left(\frac{A}{W_{click}}\right) + c\log_2\left(\frac{A}{W_{visual}}\right)$	390 [343, 437]	111 [102, 120]	11.6 [2.69, 20.5]	0.959	301	455 [389, 520]	94.2 [81.9, 107]	16.7 [4.34, 29.0]	0.898	322
#6	ID_{mv2} (segmented)	$MT = a + b\log_2\left(\frac{A}{W_{click}} + 1\right) + c\log_2\left(\frac{A}{W_{visual}} + 1\right)$	335 [286, 385]	120 [111, 129]	12.6 [3.52, 21.7]	0.963	298	405 [335, 475]	102 [89.3, 115]	18.1 [5.27, 30.9]	0.906	320
#7	ID_{mv1} (combined)	$MT = a + b\log_2\sqrt{\left(\frac{A}{W_{click}}\right)^2 + c\left(\frac{A}{W_{visual}}\right)^2}$	387 [347, 426]	121 [112, 130]	0.035 [0.011, 0.058]	0.967	295	427 [378, 476]	112 [101, 124]	0.102 [0.047, 0.157]	0.942	304
#8	ID_{mv2} (combined)	$MT = a + b\log_2\left(\sqrt{\left(\frac{A}{W_{click}}\right)^2 + c\left(\frac{A}{W_{visual}}\right)^2 + 1}\right)$	336 [295, 377]	130 [121, 140]	0.036 [0.012, 0.059]	0.970	291	381 [330, 431]	121 [109, 132]	0.104 [0.051, 0.158]	0.947	301

Table 1 shows all candidate models. Some have two regression constants, and others have three. Comparing ID_{m1} and ID_{mv1} (segmented) for example, when $c = 0$ in ID_{mv1} (segmented), these models become the same (i.e., ID_{mv1} (segmented) shows a better R^2 than ID_{m1}). Thus, we analyzed model fitness by using adjusted R^2 and Akaike's information criterion (*AIC*) [3]. A model that shows a good fit also shows a higher adjusted R^2 and a lower *AIC* [13, 29, 40][7]. As shown in Table 1, for both *Distractor* conditions, ID_{mv2} (combined) showed the best fit. Additionally, the c values in our models were small, which is consistent with the slight effect of W_{click}.

Because movement time strongly depended on clickable width, and increasing clickable width increased SD_x, we verified the model fitness of ID_e (Equation 3) per each *Distractor*. Under both *Distractor* conditions, ID_e showed the following fits: $MT = 262 + 146 ID_e$ with $R^2 = 0.937$ when *Distractor = True*, $MT = 241 + 150 ID_e$ with $R^2 = 0.858$ when *Distractor = False*. Usuba et al. [32] showed good fits, even when using the effective width. When *Distractor = False*, R^2 was below the typical threshold. Thus, the model using the effective width may need to be modified.

4.6 Discussion

We found that MT did not depend on the presence or absence of distractors (Figure 7). This result is consistent with a previous study [7] (see c/b in Table 2 in [7]). Some participants reported that they always aimed for the center of the target, regardless of whether distractors existed. This is one reason that the distractors did not affect movement times. On the other hand, the spread of clicked positions (SD_x) was affected by a *Distractor* (Figure 9). Thus, the presence of the distractors increased SD_x. Some participants reported that they performed pointing operations while relying on the highlight of the clickable width of the left distractor. They judged the size of the clickable width of the target by observing the highlight of the clickable width of the left distractor. Thus, the participants sometimes accidentally clicked on the clickable width of the distractor. We believe that this kind of operation increased SD_x.

[7]If the difference between the AICs is higher than two at least, the difference is considered sufficient [9].

Usuba el al. found that dwell and movement times were U-shaped functions. Thus, the times were fastest when the clickable and visual widths were the same, and the times increased when increasing the difference between the clickable and visual widths. [32]. We did not obtain these results (Figures 6 and 8). In their tasks, the clickable width was highlighted prior to starting a trial. Thus, the participants knew the clickable width in advance. In our task, the participants did not know the clickable width in advance. We believe that this is why different results were obtained.

For *Distractor = True*, ID_{m2} showed a good fit. However, when *Distractor = False*, owing to the model fitness of ID_{m2} having decreased, we found that the effect of W_{visual} should be considered. The model fitness of ID_{mv2} (combined) showed the best fits under both *Distractor*. Additionally, compared with ID_{mv1} (combined), we found that adding +1 improved model fitness, even if clickable and visual widths were different. In summary, we recommend using ID_{mv2} (combined). The time prediction model for different clickable and visual widths was built for the first time from our experiment, and our results extended the knowledge of previous studies.

5 EXPERIMENT 2: EFFECTS OF INTERVAL BETWEEN DISTRACTORS AND TARGET

Sometimes, UI designers create intervals between items in navigation bars such as in Figure 1b. When $W_{click} > W_{visual}$ in Figure 4, there seem to be intervals. However, the clickable width of the target touches those of the distractors. In Experiment 2, the target does not touch the distractors in either clickable or visual widths (Figure 2c). In Experiment 1, when there were intervals, the participants could predict that the clickable width was larger than the visual width. However, in Experiment 2, there were intervals between the clickable widths, and participants could not predict them. On the basis of Equation 6, we presume that increasing the intervals decreased movement times. The apparatus, participants, and measurements were the same as in Experiment 1.

5.1 Task, Design, and Procedure

In this experiment, the task (Figure 2c) included intervals (I) between the target and distractors in addition to the task of Experiment 1. As with Experiment 1, the participants clicked on the blue start area and aimed for the green target while avoiding the red distractors.

The variables of A, W_{click}, and W_{visual} were the same as those of Experiment 1. However, unlike Experiment 1, the distractors always existed (i.e., always $Distractor = True$). The I was 0, 20, 40, or 70 pixels (0, 3.41, 6.82, or 11.94 mm, respectively).

The orders of A, W_{click}, W_{visual}, and I were randomized. One *set* consisted of $2A \times 4W_{click} \times 4W_{visual} \times 4I = 128$ trials. After an introductory practice set, each participant completed seven sets to produce experimental data. A total of 10,752 trials (i.e., $2A \times 4W_{click} \times 4W_{visual} \times 4I \times 7$ sets $\times$ 12 participants) were conducted, requiring approximately 35 min per participant.

6 RESULTS

Among the 10,750 trials (two outliers), 382 errors occurred (3.55%).

6.1 Dwell Time

We observed the main effects for A ($F_{1,11} = 14.57, p < 0.01, \eta_p^2 = 0.57$), W_{click} ($F_{3,33} = 21.58, p < 0.001, \eta_p^2 = 0.66$), and I ($F_{3,33} = 33.01, p < 0.001, \eta_p^2 = 0.75$), not W_{visual} ($F_{3,33} = 0.62, p = 0.61, \eta_p^2 = 0.053$). Figure 12 shows the results of the post hoc test. We also observed the interactions for $W_{visual} \times I$ ($F_{9,99} = 4.27, p < 0.001, \eta_p^2 = 0.28$) and $W_{click} \times W_{visual} \times I$ ($F_{27,297} = 1.78, p < 0.05, \eta_p^2 = 0.14$). When W_{click} and W_{visual} were small for $W_{click} \times W_{visual} \times I$, the differences between Is were significant (Figure 13).

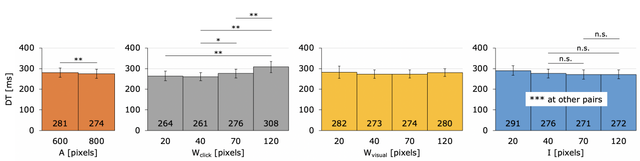

Figure 12: *DT* **vs.** A**,** W_{click}**,** W_{visual}**, and** I**.**

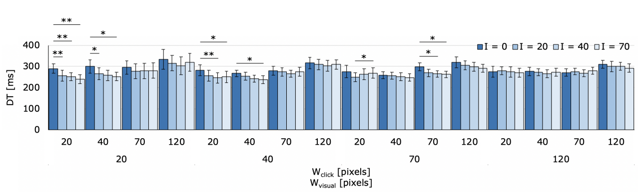

Figure 13: $W_{click} \times W_{visual} \times I$ **for** *DT***.**

6.2 Movement Time

We observed the main effects for A ($F_{1,11} = 114.77, p < 0.001, \eta_p^2 = 0.91$), W_{click} ($F_{3,33} = 160.12, p < 0.001, \eta_p^2 = 0.94$), and I ($F_{3,33} = 4.57, p < 0.01, \eta_p^2 = 0.29$), not W_{visual} ($F_{3,33} = 2.33, p = 0.092, \eta_p^2 = 0.17$). Figure 14 shows the results of the post hoc test. We also observed the interactions for $W_{click} \times W_{visual}$ ($F_{9,99} = 5.42, p < 0.001, \eta_p^2 = 0.33$) and $W_{visual} \times I$ ($F_{9,99} = 2.34, p < 0.05, \eta_p^2 = 0.18$). For $W_{click} \times W_{visual}$, increasing W_{click} increased the differences between W_{visual}s (Figure 15 left). For $W_{visual} \times I$, when $W_{visual} = 40$, the differences between Is were significant (Figure 15 right).

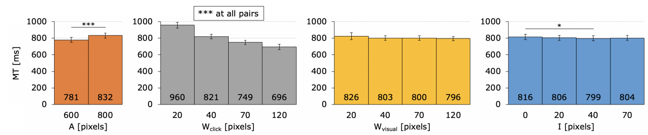

Figure 14: *MT* **vs.** A**,** W_{click}**,** W_{visual}**, and** I**.**

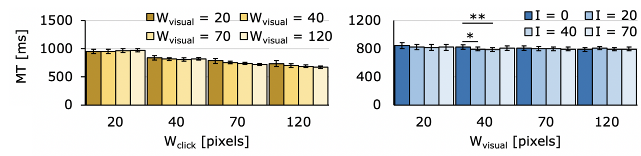

Figure 15: $W_{click} \times W_{visual}$ **and** $W_{visual} \times I$ **for** *MT***.**

6.3 Standard Deviation of x-coordinate

We observed the main effects for W_{click} ($F_{3,33} = 136.63, p < 0.001, \eta_p^2 = 0.93$), W_{visual} ($F_{3,33} = 3.12, p < 0.05, \eta_p^2 = 0.22$), and I ($F_{3,33} = 3.04, p < 0.05, \eta_p^2 = 0.22$), not A ($F_{1,11} = 2.81, p = 0.12, \eta_p^2 = 0.20$). Figure 16 shows the results of the post hoc test. We also observed the interaction for $W_{click} \times W_{visual}$ ($F_{9,99} = 3.49, p < 0.001, \eta_p^2 = 0.24$). Regarding $W_{click} \times W_{visual}$, increasing W_{click} did not increase the differences between W_{visual}.

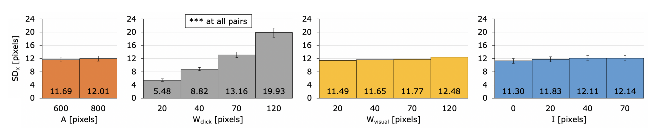

Figure 16: SD_x **vs.** A**,** W_{click}**,** W_{visual}**, and** I**.**

6.4 Error Rate

We observed the main effects for A ($F_{1,11} = 7.89, p < 0.05, \eta_p^2 = 0.42$), W_{click} ($F_{3,33} = 24.72, p < 0.001, \eta_p^2 = 0.69$), W_{visual} ($F_{3,33} = 3.53, p < 0.05, \eta_p^2 = 0.24$) and I ($F_{3,33} = 5.66, p < 0.01, \eta_p^2 = 0.34$). Figure 17 shows the results of the post hoc test. We also observed the interactions for $W_{click} \times I$ ($F_{9,99} = 2.04, p < 0.05, \eta_p^2 = 0.16$) and $A \times W_{click} \times I$ ($F_{9,99} = 2.50, p < 0.05, \eta_p^2 = 0.18$). For $A \times W_{click} \times I$, although the differences between Is were not significant, increasing the size of I almost always increased the error rate.

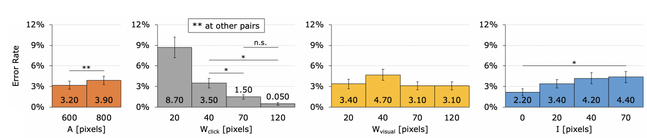

Figure 17: Error rate vs. A**,** W_{click}**,** W_{visual}**, and** I**.**

6.5 Model Fitting

As shown in Figure 14, we found that the effect of I on MT was insignificant. However, because we found some interactions related to I, we believe that considering I may improve model fitness. Thus, we decided to include I during model construction. We found the interactions for $W_{click} \times W_{visual}$ and $W_{visual} \times I$ on MT. Additionally, we observed that W_{click} and I had larger effects than did W_{visual}. Thus, we presumed that the relationship between W_{click} and W_{visual} was similar to that between I and W_{visual}. We can obtain a model (Model #3 in Table 2) by adding I in a form similar to W_{click} of Model #8 in Table 1. The range of I is presumed to be $[0, \infty]$. Thus, if we simply add I to the model, division by zero occurs when $I = 0$. Based on previous studies [20, 30], we added 0.0049, which can be rounded to 0.00 to prevent division by zero. When $I = 20$, for example, $\log_2(A/(20 + 0.0049) + 1) - \log_2(A/20 + 1) = 0.00035$. Thus, adding 0.0049 did not affect the predicted MT very much.

Considering that the effect of W_{visual} was slight, the term, $d\left(\left(\frac{A}{W_{visual}}\right)\right)$ may not contribute much to model fitness. Additionally, because the interaction for $A \times I$ was not observed, and it is convenient that the model be consistent with Model #8 in Table 1, Model #3 in Table 2 was converted to Model #4 in Table 2. In the model, when $I = 0$, for example, the logarithm term, including I, becomes $b_2 \log_2(1/0.0049 + 1)$. Thus, it is a constant. Additionally, when $I = \infty$, the logarithm term becomes $b_2 \log_2(1)$. Thus, it vanishes. That is, Model #4 in Table 2 is consistent with Model #8 in Table 1. Moreover, in the original Fitts' task where $W_{click} = W_{visual}$ and $I = \infty$ (there are no distractors), Model #4 in Table 2 can be approximated to Equation 2. Although Equation 6 can consider the position of the distractors, all distractors must have the same ID as that of the target. In Experiment 2, the distractors had the same clickable and visual width as that of the target (i.e., the distractors' ID differed from the target's ID). Thus, we built new models instead of Equation 6.

We verified the adjusted R^2 and AIC of all candidate models (Table 2). In those, we used +1 versions. The ID_{mvi2} model showed the highest R^2 and the lowest AIC. The difference between the AIC values of ID_{mvi1} and ID_{mvi2} was small. However, because ID_{mvi2} had fewer constants and was consistent with Model #8 in Table 1 and Equation 2, ID_{mvi2} was the best of the candidate models. The model fitness of ID_e ($N = 128$) was $MT = 229 + 145 ID_e$ with $R^2 = 0.870$ in Experiment 2. Similar to Experiment 1, the model using the effective width may need to be modified.

6.6 Discussion

We found that increasing I between the target and distractors slightly decreased MT (Figure 14). Additionally, although the differences were not significant, increasing I increased the spread of the clicked positions (SD_x) and error rate (Figures 16 and 17). Thus, it is possible that wide intervals allowed users to perform operations more quickly but less accurately. Moreover, the dwell time was not a U-shaped function. This is not consistent with the results found by Usuba et al. [32], but it matches those of our Experiment 1. Thus, when users do not know the size of the clickable width in advance, the dwell time may not approach the U-shaped function.

We constructed a time prediction model (Model #4 in Table 2), which showed the highest adjusted R^2 and lowest AIC. In terms of the equation form, the model was consistent with Model #8 in Table 1, as constructed on the basis of the results from Experiment 1. However, the predicted MT may not be consistent with the results of Experiment 1. In Experiment 1, although the difference between *Distractor* was not significant for MT, when *Distractor = True*, MT was smaller than that when *Distractor = False* (Figure 7). However, according to Model #4 in Table 2, the predicted MT when *Distractor = True* (i.e., $I = 0$) was larger than that when *Distractor = False* (i.e., $I = \infty$). Thus, we believe that, to apply our model to a wide range of conditions, it should be refined. On the other hand, comparing Model #4 in Table 2 with Equation 6, both show that increasing the interval between the target and distractors decreased the movement time. Thus, enlarging I does not necessarily decrease MT, and we believe that there is a threshold for the effect of I.

In Figure 1a, the partitions of the items are unclear. Based on our model, because the visual width slightly affected the movement time, if the clickable width is large, the visual width need not be (i.e., the partitions do not need to be clear as with Figure 1b). However, in Figure 1b, the clickable width is small. Thus, the existence of the intervals may not be a problem, but the clickable width should be enlarged.

In summary, although there are some limitations, we constructed a time prediction model that can consider the difference between clickable and visual widths and the intervals between the target and distractors on the basis of the results from Experiments 1 and 2.

7 MODEL FITTING FOR DATA OF EXISTING STUDIES

We verified that our model showed a good fit for Usuba et al.'s data [32, 33]. Their studies also found that movement time was affected strongly by clickable widths and slightly by visual widths. The results of their studies are similar to ours. Thus, we believe that ID_{mv2} (combined) can predict movement times for their data more accurately.

Table 3 shows the model fitness for the experiment of [33], Experiment 1 in [32], and Experiment 2 in [32]. Apart from the data of Experiment 2 in [32], ID_{mv2} (combined) showed larger R^2 and lower AIC. In Experiment 2 of [32], the range of clickable width by each visual width depended on the value of the visual width. As Usuba et al. mentioned in that paper, because the effect of visual width depended on the range of the clickable width (the effect of visual width decreased), the original Fitts' law showed high R^2. Thus, the results may also depend on the experimental condition. On the other hand, considering the difference in AIC, ID_{mv2} (combined) did not show a worse fit for Experiment 2 in [32]. In summary, ID_{mv2} (combined) showed good fits for the data of three previous studies, empirically supporting it.

8 LIMITATION AND FUTURE WORK

Optimal movement time was obtained by our ID_{mvi2} (combined) from given clickable widths, visual widths, and intervals. However, we did not find the optimal values in terms of total user performance. For example, although our model showed that increasing intervals decreased the movement time, if a navigation bar has larger intervals between items, the navigation bar becomes larger. The distance to each item is also longer, and the total movement

Table 2: Model fitting for all conditions ($N = 128$). All regression constants with 95% CIs [lower, upper].

	Model	Equation	a	b_1	c	d	b_2	adj. R^2	AIC
#1	ID_{m2}	$MT = a + b_1 \log_2 \left(\frac{A}{W_{click}} + 1\right)$	374 [351, 397]	111 [105, 117]				0.924	1234
#2	ID_{mv2} (combined)	$MT = a + b_1 \log_2 \sqrt{\left(\frac{A}{W_{click}}\right)^2 + c\left(\frac{A}{W_{visual}}\right)^2 + 1}$	314 [292, 337]	123 [118, 128]	0.054 [0.038, 0.071]			0.954	1172
#3	ID_{mvi1}	$MT = a + b_1 \log_2 \sqrt{\left(\frac{A}{W_{click}}\right)^2 + c\left(\frac{A}{W_{visual}}\right)^2 + 1} + b_2 \log_2 \sqrt{\left(\frac{A}{I+0.0049}\right)^2 + d\left(\frac{A}{W_{visual}}\right)^2 + 1}$	307 [284, 329]	123 [118, 128]	0.055 [0.038, 0.072]	-0.082 [-0.082, -0.082]	0.99 [0.28, 1.69]	0.957	1166
#4	ID_{mvi2}	$MT = a + b_1 \log_2 \sqrt{\left(\frac{A}{W_{click}}\right)^2 + c\left(\frac{A}{W_{visual}}\right)^2 + 1} + b_2 \log_2 \left(\frac{1}{I+0.0049} + 1\right)$	311 [289, 333]	123 [118, 128]	0.054 [0.038, 0.070]		1.74 [0.56, 2.92]	0.957	1165

Table 3: Model fitting for three experiments of previous studies. All regression constants with 95% CIs [lower, upper].

	Model	Equation	Experiment in [33] ($N = 24$)					Experiment 1 in [32] ($N = 32$)					Experiment 2 in [32] ($N = 32$)				
			a	b	c	adj. R^2	AIC	a	b	c	adj. R^2	AIC	a	b	c	adj. R^2	AIC
#1	ID_{m2}	$MT = a + b \log_2 \left(\frac{A}{W_{click}} + 1\right)$	263 [111, 414]	159 [134, 183]		0.901	258	486 [417, 554]	112 [94.6, 129]		0.861	336	381 [356, 406]	115 [109, 121]		0.975	291
#2	ID_{mv2} (combined)	$MT = a + b \log_2 \sqrt{\left(\frac{A}{W_{click}}\right)^2 + c\left(\frac{A}{W_{visual}}\right)^2 + 1}$	140 [-74.6, 103]	192 [179, 205]	0.0086 [0.0061, 0.011]	0.980	222	399 [329, 469]	129 [113, 145]	0.087 [0.025, 0.15]	0.914	323	362 [331, 393]	117 [111, 123]	0.16 [-0.033, 0.36]	0.977	291

time in the navigation bar may become longer. Constructing a model considering total user performance is for future work.

In actual GUIs, such as those in Figure 1, the positions of distractors were vertical or horizontal, the visual width by each object differed, and the objects had certain heights. Our model was a baseline model for 1D pointing tasks. More practically, it should be refined to consider the above factors.

In this study, the participants could not know the target clickable width in advance. When users use a new application, although they do not know the clickable width at first, they roughly grasp it by getting used to the application. Thus, our study only simulated users' first use. However, our model could be applied to a situation where users know the clickable width in advance [32, 33]. Therefore, we believe that our model does not have a limitation on whether users can know the clickable width in advance.

In touch interfaces, the motor width is not highlighted before touching it because users' fingers hover on the screen; in finger pointing, it is impossible that the users behave as seen in our experiments. However, the movement time observed in [34] (finger-pointing study) is similar to this data. Thus, we believe that our model can predict the movement time of finger pointing.

9 CONCLUSION

We conducted two experiments to investigate the effect of distractors and intervals between a target and its distractors. Considering R^2 and AIC, we constructed a model that can consider clickable and visual widths and intervals. Our model showed good fits for not only the data of our two experiments, but also those of three previous studies. Therefore, our model was shown to be empirically correct. Our model will allow designers to obtain optimal movement times based on the clickable and visual widths and intervals.

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