Predicting Text Selection Time and Effort on Smartphones from Selection Characteristics

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Abstract

This work investigates how text selection characteristics, such as distance, text length, and layout, affect text selection performance. Using 1,330 selection instances, we analyzed their relationships with two outcomes: selection time and selection effort. Spearman correlations showed weak associations with selection time but moderate correlations with effort. Stepwise regression revealed that distance-related characteristics jointly predicted selection time, while selection effort was better predicted using a combination of length, distance, and layout characteristics. Overall, selection effort proved easier to predict than selection time.

Keywords

Text Entry, Error Correction, Text Editing, Text Selection, Modeling

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1 Introduction

Mobile users spend a significant amount of time entering and interacting with text on their devices, and text selection plays a key role in these interactions. Users frequently select text to cut, copy, paste, format, or reposition it within a document [7]. Prior research has shown that text selection on mobile devices can be a challenging task, primarily due to the "fat finger problem" [10]–the difficulty of accurately positioning the cursor with a finger on small screens and tightly spaced text. This often leads to increased effort, user frustration, and frequent errors. While previous studies have explored text interaction behaviors, they have largely done so as part of broader tasks such as editing or formatting, rather than examining text selection as an isolated behavior [7].

Because designing, developing, and evaluating new text interaction methods is often a slow and resource-intensive process, there is growing interest in predicting performance outcomes early on, before investing in high-fidelity prototypes. This also provides access to an evaluation approach when participant recruitment is difficult. Although extensive research exists on predicting performance for tasks like text entry [5] and error correction [1], text selection has remained underexplored. It is commonly assumed that selection time and effort increase with text length, and Fitts' Law suggests that smaller font sizes could lead to slower and more error-prone selections [8]. However, these assumptions have not been empirically validated. Moreover, our own observations suggest that selection time and effort are likely influenced by multiple interacting factors, making simplistic models insufficient.

In this work, we investigate whether text selection performance on mobile devices can be predicted based on specific characteristics of the selection: distance (Euclidean, horizontal, and vertical), text length (character or word count), and layout (e.g., number of lines spanned). Our contributions are twofold. First, we provide a deeper understanding of which selection characteristics impact performance, offering a foundation for developing predictive models to support tasks like text editing and overall text entry. Second, our findings can inform design guidelines for mobile interfaces to reduce the effort and frustration associated with selection. Most importantly, we hope this work lays the groundwork for future research focused on modeling and improving text selection behavior.

2 Text Selection on Mobile Devices

Modern mobile operating systems allow users to position the text cursor directly by touching the screen. The cursor initially appears where the finger touches down, and sliding the finger moves the cursor accordingly. To support precise placement, a magnifier window is typically shown, revealing the text beneath the finger. Text can also be selected by long-pressing on a word (typically for 500–1,000 ms), which automatically highlights the word and brings up text selection handles [2]. Users can then drag these handles to adjust the start and end points of the selection (Fig. 2).

Some virtual keyboards offer enhanced cursor control features. For example, users can press and hold the spacebar and slide their finger left or right to move the cursor horizontally. Others allow the entire keyboard to function as a trackpad when the user long-presses or applies extra force to the spacebar.

3 Data Collection

The data for this research were drawn from an existing study [7] originally aimed at comparing a novel gestural approach to text editing and formatting on smartphones with a conventional method. In both conditions, participants completed a series of editing and formatting tasks (e.g., cut, copy, bold, italic), each requiring them to first select text. Because the experimental application logged all

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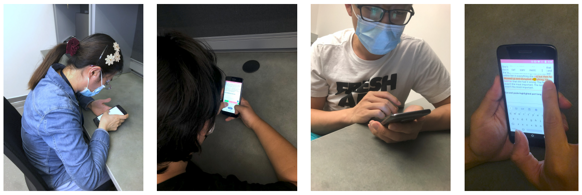

Figure 1: Participants selecting text in the user study.

interactions, it captured rich data on text selection that had not been previously analyzed.

Participants. Twelve volunteers (aged 20–32 years, M = 24.8, SD = 4.1) participated in the study. They were all experienced mobile users (M = 8.0 years, SD = 3.8). Ten of them owned an iOS device, while the remaining two used an Android-based device. All participants were right-handed mobile users.

Apparatus. The study used a Motorola Moto G^5 Plus smartphone (150.2 × 74 × 7.7 mm, 155 g, 1080 × 1920 pixels) running Android OS 7.0. A custom app presented tasks and logged all interactions with timestamps. The interface included a paragraph, a task prompt, a text area for pasting, and a virtual keyboard (Fig. 1). The text was displayed in Roboto font at 18sp (2.86 mm or 13.50 px).

Procedure. In the baseline condition, participants were asked to complete 1,344 editing and formatting tasks. However, in 14 instances (1% of the data), participants did not perform the selection task as required. These cases were excluded from the analysis. The application presented one task at a time. To reduce visual scanning time, relevant parts of the paragraphs were highlighted in color. Participants were asked to complete the tasks in a seated position, as quickly and accurately as possible. Error correction was recommended but not required. After completing each task, participants tapped a button to see the next task.

4 The Dataset

We collected data from a total of 1,330 text selection incidents, spanning over 2.5 hours of interaction. The shortest selection took approximately 0.68 seconds, while the longest lasted 1.42 minutes (M = 6.92 seconds, SD = 6.85). Across all incidents, participants selected 109,423 characters (M = 82.27, SD = 73.44), 20,237 words (M = 15.22, SD = 13.63), and 3,709 lines (M = 2.79, SD = 1.83). Each task involved selecting between 7 and 239 characters, 2 to 46 words, and 1 to 7 lines. In total, participants performed 27,739 actions to complete these selections, with a minimum of 3 and a maximum of 171 actions per task (M = 20.86, SD = 16.33).

4.1 Selection Performance

We calculated two metrics to evaluate text selection performance:

Selection Time: The duration, in seconds, that participants took to complete a selection task. This includes any time spent correcting mistakes during the selection process. The selection was considered complete when the participant chose a post-selection action, such as Cut, Copy, or Paste.

Selection Effort: Measured by the number of actions performed to complete a selection task. This metric aligns with the "actions per task" measure commonly used in interaction research [6]. Actions include taps, double-taps, slides, finger movements, or any other gestures used during the selection process. It also accounts for corrective actions, such as adjusting selection handles or restarting the selection.

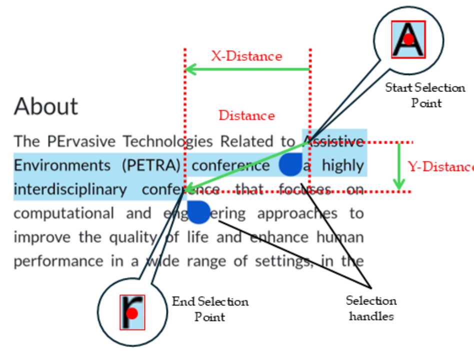

Figure 2: Calculation of the three distance characteristics. Distances are computed using the center positions of the first and last selected characters, indicated by red dots.

4.2 Selection Characteristics

To facilitate correlation analysis, we identified the following key characteristics of each text selection.

Number of Characters (C): The total number of characters included in the selection, including symbols and the space character.

Number of Words (W): The number of complete or partial words in the selection. A partial word is counted as one word. For example, selecting only "confer" from the word "conference" is considered one word (Fig. 2).

Number of Lines (L): The total number of lines that the selection spans.

X-Distance (X): The horizontal distance, in pixels, along the x-axis between the start and end points of the selection, measured as the center positions of the first and last selected characters.

Y-Distance (Y): The vertical distance, in pixels, along the y-axis between the start and end points of the selection.

Distance (D): The Euclidean distance, in pixels, between the start and end points of the selection. Fig. 2 illustrates how these distances are calculated.

5 Spearman Correlation Results

We conducted a Spearman rank correlation (ρ) analysis on the study data, as this method does not assume linearity or a normal distribution. Table 1 presents the correlation results. Spearman correlation coefficients are commonly interpreted as negligible ($\rho \leq 0.10$), weak ($\rho \approx 0.10$–0.39), moderate ($\rho \approx 0.40$–0.69), and strong ($\rho \geq 0.70$) [9]. We also performed post hoc power analyses ($1-\beta$) for statistically significant results using G*Power [4], based on the α error probability observed in the Spearman rank correlation and a sample size of N = 1,330 paired observations, all of which exceeded the $1 - \beta \geq 0.8$ threshold for high power [3].

Table 1: Results of statistical tests on text selection data. Orange and blue ticks indicate weak and moderate correlations, respectively, while green ticks mark statistically significant ones. Overall moderate relationships are shaded blue. Columns represent characteristics from Section 4.2. As Spearman's correlation is symmetric, predictor and response roles are interchangeable.

		Characters	Words	Lines	X-Distance	Y-Distance	Distance
Selection Time	p	$< .001$ ✓	$< .001$ ✓	$< .001$ ✓	$< .001$ ✓	$< .001$ ✓	$< .001$ ✓
	ρ	.369 ✓	.357 ✓	.285 ✓	.196 ✓	.289 ✓	.332 ✓
Selection Effort	p	$< .001$ ✓	$< .001$ ✓	$< .001$ ✓	$< .001$ ✓	$< .001$ ✓	$< .001$ ✓
	ρ	.505 ✓	.493 ✓	.483 ✓	.155 ✓	.476 ✓	.368 ✓

Table 2: Overall fit statistics of the final linear regression models predicting selection performance (outcomes) from selection characteristics (predictors). The abbreviations C, W, L, X, Y, and D correspond to the characteristics described in Section 4.2.

Dependent Variable	Model	Predictor	R^2	Adjusted R^2	Standard Error	F	p
Selection Time	1	D	.056	.055	6.66	78.73	$< .001$
	2	D, X	.060	.059	6.65	42.49	$< .001$
	3	D, X, L	.065	.063	6.63	30.70	$< .001$
Selection Effort	1	Y	.101	.101	15.49	149.95	$< .001$
	2	Y, W	.151	.150	15.06	118.28	$< .001$
	3	Y, W, D	.200	.198	14.62	110.58	$< .001$
	4	Y, W, D, X	.207	.205	14.56	86.47	$< .001$
	5	Y, W, D, X, C	.210	.208	14.54	70.60	$< .001$
	6	Y, W, D, X, C, L	.213	.210	14.52	59.74	$< .001$

Selection Time. A Spearman rank correlation analysis revealed weak positive correlations between selection time and all examined selection characteristics (Table 1). These results suggest that selection time tends to increase as the amount of text and the distance between the start and end points increase.

Selection Effort. A Spearman rank correlation analysis showed moderate positive correlations between selection effort and text length metrics, including the number of characters, words, and lines, as well as Y-Distance (Table 1). Weak positive correlations were observed with X-Distance and overall Euclidean Distance.

Discussion. In this analysis, none of the individual selection characteristics emerged as strong predictors of text selection performance. While there were statistically significant positive relationships between selection time and all selection characteristics, suggesting that longer text and greater selection distances tend to increase selection time, these relationships were weak. In contrast, selection effort showed statistically significant positive relationships of moderate strength with text length-based metrics, indicating that the number of actions required to select text increases with text length. These metrics may therefore serve as useful estimates of effort. We also found a moderate, statistically significant positive relationship between selection effort and Y-Distance, and weak positive relationships with other distance-based metrics. This suggests these spatial characteristics may influence selection effort to some extent.

6 Multiple Linear Regression Results

Interestingly, the scatter plots revealed distinct clusters of data points (Fig. 3), suggesting that no single characteristic fully explains the variation in selection performance. Hence, we used stepwise multiple linear regression to model selection performance based on a combination of characteristics, adding and removing predictors based on their significance.

Selection Time. Distance was the strongest single predictor of selection time. This matches the correlation results, where Distance showed a statistically significant and relatively higher Spearman's ρ than the other characteristics. As expected, adding more predictors improved the model's ability to explain variation. The best model (Model 3) included Distance, X-Distance, and number of lines, with a small-to-medium effect size [3].

Selection Effort. In contrast to selection time, Y-Distance alone emerged as a statistically significant predictor of selection effort, with a medium-to-large effect size. This is consistent with the correlation analysis, where Y-Distance showed a moderate, statistically significant relationship with effort. Adding additional predictors further improved the model's fit. The best-performing model included all selection characteristics and yielded an R^2 of 0.21, approaching a large effect size. These results suggest that selection effort is easier to predict than selection time.

7 Conclusion & Future Work

This work explored how text selection performance on mobile devices is affected by text selection characteristics. Correlation and stepwise regression analyses showed that selection effort is more reliably predicted than selection time, with multiple characteristics influencing performance. In future work, we will examine how device-holding posture influences selection speed and effort. We also aim to develop machine learning models to predict selection tasks in diverse settings, with the goal of assisting users, particularly

(a) Characters × Selection Time (b) Words × Selection Time (c) Lines × Selection Time

(d) Characters × Selection Effort (e) Words × Selection Effort (f) Lines × Selection Effort

(g) X-Distance × Selection Time (h) Y-Distance × Selection Time (i) Distance × Selection Time

(j) X-Distance × Selection Effort (k) Y-Distance × Selection Effort (l) Distance × Selection Effort

Figure 3: Scatter plots showing the relationships between text selection performance metrics and selection characteristics.

those with limited motor abilities or situational impairments, in completing selections more efficiently.

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