Flick-in: Japanese Text Entry Method for Indirect Touch Using Bezel-Initiated Swipe

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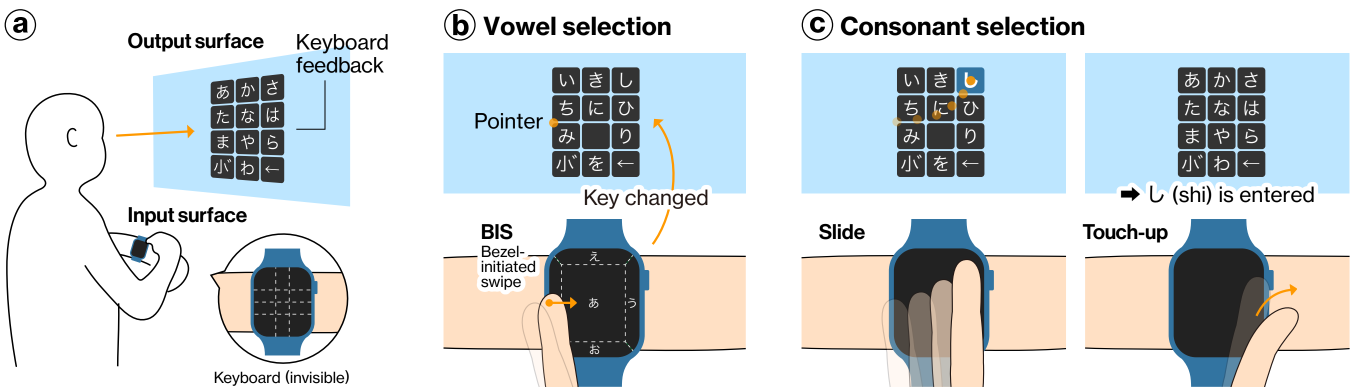

Figure 1: Flick-in is a Japanese text entry method for indirect touch. a) Users enter text using a smartwatch keyboard as the input surface while watching keyboard feedback displayed on the output surface. b) When users perform a bezel-initiated swipe (BIS) gesture on the left bezel, the 'i' vowel is selected and the keyboard layout updates to display consonant keys corresponding to 'i.' Simultaneously, a pointer indicating the user's touch position on the keyboard appears on the output surface. c) Users select a target key by sliding their fingers across the keyboard feedback to position the pointer over the target key, then lifting their fingers (touch-up) from the input surface to complete the selection.

Abstract

We present Flick-in, a Japanese text entry method for indirect touch on a smartwatch. Indirect touch is performed without looking at the input surface, which makes it difficult to touch down accurately at the correct location. This difficulty limits the usability of conventional Japanese text entry methods, which require visual confirmation of the input surface. In contrast, few Japanese text entry methods have been proposed specifically for indirect touch. In Flick-in, users first select a vowel using a bezel-initiated swipe, followed by selecting a consonant using a touch-up gesture while observing the output surface. This makes Japanese text entry with indirect touch feasible. We conducted two studies to evaluate the performance of Flick-in using an external display and a mixed reality (MR) environment as output surfaces. The results showed a text entry speed of 29.5 CPM with a total error rate (TER) of 10.0% on the external display and 36.5 CPM with a TER of 6.14% in the MR environment.

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CCS Concepts

• **Human-centered computing** → **Text input**; *Touch screens*; *Mobile devices.*

Keywords

Smartwatch, Mixed Reality, Virtual Reality, Flick Text Entry, Touch Screen, Touch Typing

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Vowel \ Basic consonant	あ a	か k	さ s	た t	な n	は h	ま m	や y	ら r	わ w
あ a	あ a	か ka	さ sa	た ta	な na	は ha	ま ma	や ya	ら ra	わ wa
い i	い i	き ki	し shi	ち chi	に ni	ひ hi	み mi		り ri	を wo
う u	う u	く ku	す su	つ tsu	ぬ nu	ふ hu	む mu	ゆ yu	る ru	ん n
え e	え e	け ke	せ se	て te	ね ne	へ he	め me		れ re	ー
お o	お o	こ ko	そ so	と to	の no	ほ ho	も mo	よ yo	ろ ro	

Figure 2: A table of basic Japanese kana letters composed of basic consonant and vowel pairs.

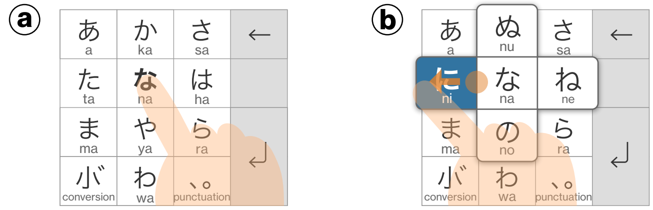

Figure 3: Keyboard layout and operation of the Flick method. a) Consonant selection with the touch-down gesture. b) Vowel selection with the flick gesture.

1 Introduction

Text entry on smart TVs and virtual/mixed reality (VR/MR) systems using head-mounted displays (HMDs) has become a common interaction scenario [21, 32, 49]. For example, users may post comments while watching videos on smart TVs or send messages while looking at another user's avatar in VR conversations. However, these scenarios pose challenges for conventional text entry methods. Pointing at an on-screen keyboard using handheld controllers requires large key sizes to ensure input precision [35], which can obstruct the underlying content. On the other hand, using external devices such as smartphones or smartwatches forces users to shift their visual attention between such devices and the display.

One possible approach to address these issues would be *indirect touch typing* [1, 30, 39, 68, 72, 73]. Indirect touch refers to interactions using a touch surface (input surface) and a display (output surface) that is separated from the touch surface [8, 14, 57, 66, 67, 71]. While traditional indirect touch scenarios involve trackpads or pen tablets as input surfaces [8, 9, 14], indirect touch is also well-suited for interactions with smart TVs (e.g., Apple TV 4K 1st generation[1] and SONY RMF-TX100J[2]) and VR/MR environments[3] [42]. Indirect touch typing (Figure 1a) extends indirect touch interaction to text entry. It has the potential to allow users to maintain their gaze on the output surface while interacting with an on-screen keyboard [14].

To achieve indirect touch typing, some methods display an on-screen keyboard (keyboard feedback) and a pointer on an output surface and require users to release their finger (touch-up gesture) for selection [1, 27, 30, 68]. When users touch the input surface with their finger (touch-down gesture), a pointer indicating the touched position on the input surface appears on the output surface. Users then move their finger while observing the pointer and select a target key by a touch-up gesture when the pointer is positioned in the key. In indirect touch, an accurate touch-down gesture on a target key is challenging, as users perform it without looking at an input surface [71]. Indirect touch typing methods allow for accurate text entry by relying on precise touch-up gestures rather than on imprecise touch-down gestures.

Although many indirect touch typing methods have been proposed, most are primarily designed for English using QWERTY keyboards; there is a lack of research on methods for Japanese. Japanese text entry is fundamentally based on 50 Japanese syllabary letters (*kana* letters), which can be transcribed into a combination of ten basic consonants (a, k, s, t, n, h, m, y, r, w) and five vowels (a, i, u, e, o) (Figure 2). Since the input procedure using QWERTY keyboards requires two key selections per kana letter, its text entry efficiency is relatively low. To improve efficiency, a text entry method based on flick (*Flick method*) has been widely adopted on handheld devices with a touchscreen, particularly among younger users [43] (Figure 3). In the Flick method, users first perform a touch-down gesture on the target consonant key and then a touch-up gesture to input the 'a' vowel or a flick gesture in the corresponding direction (i: left, u: up, e: right, o: down) to input the 'i', 'u', 'e', or 'o' vowels. This design allows users to enter a kana letter with a single stroke. However, since it requires precise touch-down on a target consonant key, it is not well suited to indirect touch typing.

In this paper, we present *Flick-in*, a Japanese kana text entry method for indirect touch using a smartwatch as the input surface (Figure 1). In Flick-in, the order in which a consonant and a vowel are input is reversed compared to the Flick method. Users first select a vowel by performing a slide-in gesture from the smartwatch bezel to the smartwatch touchscreen (bezel-initiated swipe, BIS) [70] or a touch-down gesture near the center of the touchscreen (Figure 1b). Subsequently, they input a consonant by sliding their finger on the input surface to a target consonant key and then performing a touch-up gesture while observing the output surface (Figure 1c). Since users can perform both BIS and touch-down gestures roughly and select a consonant using touch-up gestures, this design realizes accurate kana text entry in indirect touch scenarios.

The contributions of this paper are as follows:

- Presenting the design and implementation of Flick-in, a Japanese kana text entry method for indirect touch, with the implementation of Flick-in published on GitHub[4].
- Evaluating the performance of Flick-in in both direct and indirect touch scenarios using an external display as the output surface (Study 1), which shows that Flick-in achieved text entry with significantly higher accuracy and a text entry speed comparable to the Flick method in indirect touch.
- Evaluating the effects of user posture and keyboard feedback size on the performance of Flick-in in an MR environment (Study 2), which demonstrates that Flick-in maintains stable typing across various postures even with small keyboard feedback size for an unobstructed field of view.

[1]https://support.apple.com/en-us/111929 (Access: 2025-06-07)
[2]https://pur.store.sony.jp/parts/products/tv-remote_prt/RMF-TX100_purchase/ (Access: 2025-06-07)
[3]https://tech.moverio.epson.com (Access: 2025-06-07)
[4]https://github.com/inaniwaudon/flick-in

2 Related Work

This section reviews related work on indirect touch, Japanese text entry methods, and smartwatch-based touch gestures.

2.1 Indirect Touch

The characteristics of indirect touch have been investigated [57, 71]. For example, Jérémie et al. [14] showed that targeting performance is not affected by the scale of the input-output surface, while the aspect ratio is crucial. In addition, various interactions with indirect touch using lap [42], state switching [67], and fingertip tracking [8] have been proposed. Furthermore, indirect touch has been combined with gaze for a range of purposes, such as touch interaction [47, 66], text selection [52], pointer alignment [40], and mode switching [46].

Text entry methods designed for indirect touch employing pointer, gesture typing, and statistical decoding algorithms have been proposed. Pointer-based methods [1, 27, 30, 68] display a pointer on the output surface, which allows users to select keys via the pointer. Gesture typing [72] uses continuous stroke input to trace over virtual keys. Statistical decoding algorithms [39, 73] have been employed to improve input accuracy. However, these methods are primarily designed for English text entry. To the best of our knowledge, Flick-in is the first method explicitly designed with the focus on Japanese text entry for indirect touch.

2.2 Japanese Text Entry Methods

2.2.1 General Methods. Japanese text consists of kana letters (*hiragana* and *katakana*) and *kanji* characters. Since each kanji character's phonetic value can be written with one or more kana letters, users first enter a sentence or phrase in hiragana and then convert it to katakana or kanji using a conversion system such as POBox [41] or IMEs [16, 29]. This paper focuses on hiragana entry, and unless otherwise specified, "kana" refers to hiragana.

For Japanese text entry on PCs, a QWERTY keyboard is most commonly used, in which users type the consonant and vowel to enter a kana letter. On the other hand, for handheld devices with a touchscreen, the keypad layout is the de facto standard [4]. It consists of keys arranged in a 3×4 grid, ten of which are the keys corresponding to the basic consonants from 'a' to 'w'. This layout supports the Flick method.

2.2.2 Methods for Smartwatches. For commercial smartwatches, Japanese voice-to-text entry is commonly used. However, voice input is difficult to use in noisy environments and public spaces [53]. Additionally, although such smartwatches support the Flick method, it is prone to the fat-finger problem [61] and screen occlusion [18] due to the small screen size of smartwatches.

To mitigate these problems, Japanese text entry methods for smartwatches using slide-in or flick gestures from consonant keys along the bezel have been proposed [3–5, 63]. For example, in PonDeFlick [3, 4], users enter a kana letter by touching a consonant key and then performing a flick gesture in the same direction as in the Flick method. This design demonstrated the effectiveness of incorporating gestures common to the Flick method. However, using these methods with indirect touch is challenging as they require accurate touch-down gestures. Inspired by their design, we redesigned the Flick method to suit indirect touch.

2.2.3 Eyes-free Text Entry. Eyes-free Japanese text entry methods have been proposed [6, 13, 24, 65]. Since eyes-free text entry methods allow users to enter text without referring to either the input or output surface, they can be used in indirect touch scenarios.

However, their practical usability is limited due to difficulties in error correction and kana-kanji conversion. Since multiple kanji characters often correspond to a single kana text (e.g., "shikou" corresponds to "嗜好" (preference), "思考" (thinking), and "至高" (supreme)), kana-kanji conversion is necessary to select the desired kanji. However, performing kana-kanji conversion without visual support is challenging, which restricts existing eyes-free Japanese text entry methods to entering only kana letters. In contrast, indirect touch typing can provide feedback, which enables error correction and kana-kanji conversion. For these reasons, we developed a text entry method specifically designed for indirect touch.

2.3 Smartwatch-based Touch Gestures

Similar to Flick-in, which uses touch gestures on a smartwatch to interact with an output surface separate from the input surface, previous studies have used touch gestures on smartwatches to interact with remote displays and VR/MR environments [12, 36, 37, 49, 55, 60]. In addition, previous studies have found that touch gestures initiated from the bezel enable users to operate a touchscreen without looking at it [26, 31, 54, 58], especially on smartwatches [12, 17, 33, 36, 37, 44, 45, 48, 50, 51, 70, 74]. These gestures leverage the haptic feedback that users feel when touching the bezel, which allows them to confirm that they have performed the correct gesture without looking at the device. For example, Wong et al. [70] investigated the performance of BIS—a swipe gesture initiated from the bezel (i.e., sliding in from the bezel)—on circular smartwatches. They reported that 6-directional BIS can be performed with an accuracy of 93.34%. They also demonstrated an example application for English text entry using BIS with the TouchOne keyboard [64]. Based on these studies, Flick-in adopts BIS on a smartwatch for vowel selection.

3 Flick-in

Flick-in is a Japanese kana text entry method for indirect touch using a rectangular smartwatch as the input surface. Users can complete text entry without looking at the input surface by relying on a pointer that indicates the position of their touch on the input surface, along with the keyboard feedback displayed on the output surface (Figure 4). Flick-in uses a keyboard layout identical to that of the Flick method, which has been widely adopted for Japanese text entry. In its initial state, the keyboard consists of the following 12 keys arranged in a 3×4 grid: 'あ' (a), 'か' (ka), 'さ' (sa), 'た' (ta), 'な' (na), 'は' (ha), 'ま' (ma), 'や' (ya), 'ら' (ra), '小゛' (conversion key), 'わ' (wa), and '←' (backspace) (Figure 4a).

Flick-in allows users to select a vowel and a consonant in sequence to enter a kana letter with a single stroke.

3.1 Vowel Selection

Users select a vowel using either a touch-down gesture or BIS. When the target vowel is 'a,' users perform a touch-down gesture near the

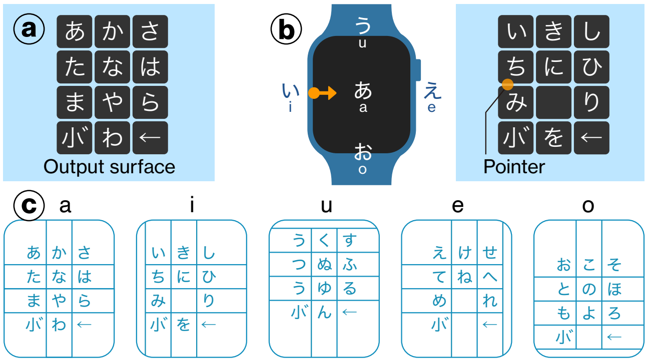

Figure 4: Keyboard of Flick-in. a) Keyboard layout in its initial state. b) Correspondence between the bezel and vowels, and keyboard layout corresponding to 'i'. When a vowel is selected, the keyboard layout updates accordingly, and a pointer is displayed. c) Consonant key arrangement.

center of the smartwatch touchscreen. When the target vowel is 'i,' 'u,' 'e,' or 'o,' users slide their finger from the corresponding bezel into the center of the touchscreen. When the smartwatch faces the user's face, the left bezel corresponds to 'i,' the upper bezel to 'u,' the right bezel to 'e,' and the bottom bezel to 'o' (Figure 4b). This arrangement is designed to match the vowel arrangement of the Flick method (Figure 3b) so that users familiar with it can adapt easily to Flick-in. If users select an unintended vowel except 'a', they can cancel the input by returning their finger to the bezel where the BIS began; once 'a' has been selected, the input cannot be canceled. Given that 'a' (23.42%) is the second most frequent vowel after 'u' (23.47%) [62] and the Flick method maps a touch-up gesture to 'a', we mapped the touch-down gesture, simpler and thus quicker than BIS, to 'a'. This design would minimize the time for entering frequently occurring kana letters whose vowels are 'a', thereby minimizing the time for re-entering the intended letter.

Previous studies have reported that eyes-free BIS with six directions on circular smartwatches can be performed with high accuracy (93.34%) [70] and suggest that rectangular smartwatches could achieve similar accuracy. Therefore, with the design assigning a vowel to each BIS direction, users could accurately select a vowel without looking at the input surface.

3.2 Consonant Selection

After a vowel is selected, the keyboard feedback on the output surface updates to display the keys corresponding to the kana letters with the selected vowel. For example, when users select the 'i' vowel, the keys change to 'i,' 'ki,' 'shi,' 'chi,' 'ni,' and so on (Figure 4b). Additionally, to reduce finger movement and facilitate key selection at the edges, the keyboard shifts in the direction of the bezel where the BIS began. Furthermore, the area of the keys outside the keyboard extends to the edge of the touchscreen (Figure 4c).

The pointer indicating the touch position is also displayed on the output surface (Figure 1b). Users slide their fingers on the touchscreen to move the pointer to the target consonant key while observing the keyboard feedback and the pointer on the output surface. Then, users perform a touch-up gesture to select the consonant.

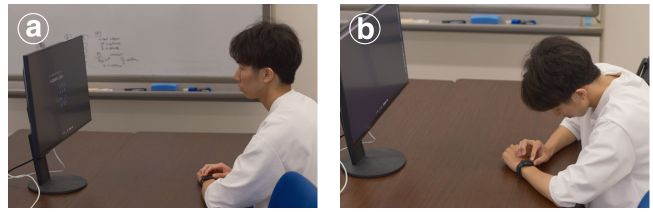

Figure 5: *Touch* conditions. a) *Indirect*. b) *Direct*.

3.3 Entry of Special Kana Letters

Flick-in allows users to enter special kana letters such as *small kana*, *voiced letters*, and *semi-voiced letters* by selecting the conversion key ('小゛' key) after entering a kana letter. Once a kana letter has been entered, the keyboard returns to its initial state. Since the conversion key is always present on the keyboard regardless of the vowel input, users can initiate the conversion using a touch-down gesture or BIS in any direction. They then slide their fingers to move the pointer to the conversion key and select it by a touch-up gesture. When the conversion key is selected, the previously entered kana letter changes to its corresponding small kana, voiced letter, or semi-voiced letter. For example, if users enter 'ha' and then select the conversion key, 'ha' will change to 'ba', the voiced letter of 'ha.' Selecting the conversion key once more will change it to 'pa', the semi-voiced letter of 'ha.' Selecting the conversion key once more will revert it to 'ha.'

4 Study 1

We conducted a user study (Study 1) to evaluate the typing performance of Flick-in in comparison with the Flick method and to examine its use in both indirect and direct touch scenarios. In the study, we used an external display as the output surface. The study took approximately 120 minutes per participant.

4.1 Participants

This study involved 12 participants (one female, 11 males; mean age: 22.8 years, *SD*=1.1 years; ID: P1–P12) from the authors' laboratory as volunteers. Eleven were right-handed, and one was left-handed. All participants reported using smartphones daily, and three reported using smartwatches daily. Regarding Japanese text entry methods on smartphones, ten reported using the Flick method daily, and two reported using a QWERTY keyboard daily.

4.2 Apparatus

We used a smartwatch (Apple Watch Series 9, 41 mm model), a laptop PC (MacBook Air, M1 2020), and a 27-inch display (EIZO, FlexScan EV2785) as the external display. The smartwatch had a square-shaped touchscreen with a resolution of 326 ppi. The software used in the study consisted of a smartwatch application and a PC application (Figure 6). The smartwatch application was implemented in Swift for watchOS; the PC application was implemented in Swift for macOS. The smartwatch application transmitted touch coordinates and input sentences to the PC application wirelessly via Bluetooth Low Energy (BLE).

Figure 6: Display for each *Touch* condition. a) The external display in *Indirect*. b) The smartwatch touchscreen in *Direct*.

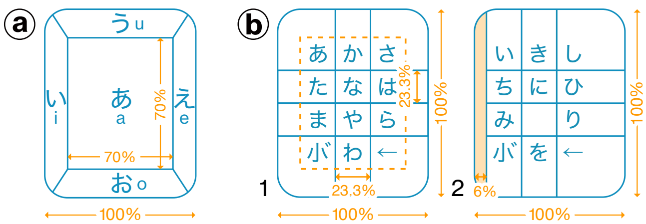

Figure 7: Input detection in *Indirect* × *Flickin*. a) Vowel areas. b) Consonant key areas: b1) for the 'a' vowel, and b2) for the 'i' vowel. The cancellation area is shown in orange.

4.3 Design

We employed a within-subjects design with two independent variables: *Touch* (*Indirect*, *Direct*) and *Method* (*Flickin*, *Flick*).

Touch represents the type of touch interaction (Figure 5). In *Indirect*, the output surface was separate from the input surface, with the external display serving as the output surface. Participants entered text by touching the smartwatch touchscreen while looking at the external display (Figure 5a). In *Direct*, the output surface was the same as the input surface, with the smartwatch touchscreen serving as both surfaces. Participants entered text by touching the smartwatch touchscreen while looking at it (Figure 5b); thus, the external display was not used.

Method consists of two text entry methods. *Flickin* is our method, which was described in Section 3. *Flick* is the Flick method described in Section 1, which we implemented as the baseline.

The order of the conditions (combinations of *Touch* and *Method*) was counterbalanced using a Latin square. All participants engaged in four sessions; each corresponded to one condition. In each session, participants performed a text entry for 28 sentences. In total, 1,344 data points (2 *Touches* × 2 *Methods* × 28 sentences × 12 participants) were collected.

4.4 Implementation

4.4.1 Touch. In *Indirect*, the width and height of the keyboard on the input surface were 70% of the touchscreen width and height, which is the same size as the standard keyboard of the Flick method of watchOS. The width and height of the keyboard feedback were 78 mm × 93 mm (Figure 6a). The aspect ratio of the keyboard feedback was almost the same as that of the smartwatch keyboard. This design was chosen because differences in aspect ratio between the input and output surfaces would affect user targeting performance [14].

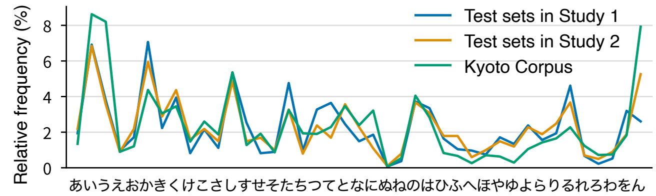

Figure 8: Frequency of kana letters.

In *Direct*, the width of the keyboard was 70% of the touchscreen width, while its height was 42% (Figure 6b). The height was reduced compared to *Indirect* because a task sentence and input text were displayed above the keyboard.

4.4.2 Method. The input detection of *Flick* is the same in both *Indirect* and *Direct*. In *Flick*, as described in Section 1, the consonant corresponding to the touched-down key is selected (Figure 3a). At the same time, the keyboard feedback updates to display vowel keys (Figure 3b). When a touch-up gesture is performed within the center key, the 'a' vowel is selected; when it is performed outside the center key, the vowel corresponding to the direction of the finger's trajectory is selected. Users can enter special kana letters by tapping the conversion key after entering a kana letter.

Flickin has differences in the input detection between *Indirect* and *Direct*. In both *Indirect* and *Direct*, we divided the touchscreen into five areas to detect vowel input. The 'a' area fits within the keyboard; the area outside of the keyboard is divided into four quadrants along the bezel, each corresponding to the vowels 'i,' 'u,' 'e,' and 'o' (Figure 7a in *Indirect*). When a touch-down gesture is performed within the 'a' area, 'a' is selected; when a finger's trajectory crosses one of the four quadrants toward the inside of the keyboard, the corresponding vowel is selected. Then, the keyboard layout changes into the one for consonant input (Figure 7b in *Indirect*). In both *Indirect* and *Direct*, when a touch-up gesture is performed, the consonant corresponding to the touched-up location is selected.

In *Flickin*, a touch-up gesture within the cancellation area cancels the input. In *Indirect*, except when the 'a' vowel is selected, the keyboard shifts to the bezel corresponding to the selected vowel so that 6% of the screen size along the bezel becomes the cancellation area (Figure 7b2), and the keys stretch to the edge of the touchscreen excluding the cancellation area. In *Direct*, the keyboard does not shift regardless of the selected vowel, and the area outside the keyboard becomes the cancellation area. The sizes of keys and the 6% cancellation area were determined according to the results of the pilot study with the authors.

In both methods, vibration feedback was provided when a key was touched, and the key's color changed while it was being touched. In *Flickin*, vibration feedback was also provided when the finger moved to a different key.

4.5 Sentence Sets

We created four kana sentence sets to provide different sentence sets (see the supplemental material) for the four conditions. Each sentence set consists of one set for practice (practice set) and one set for data collection (test set). A practice set consists of 12 sentences; a test set consists of 28 sentences (e.g., "はるはわかれのきせつ" (Spring is the season of farewells) and "ひとりぐらしをはじ

める" (I'm going to start living alone from now on)). The length of each sentence is between 10 and 14 letters, with an average of 12 letters. A test set contains a total of 336 letters. The test sets' correlation coefficient with the Kyoto Corpus [34], a Japanese text corpus based on newspaper articles, is 0.71. Figure 8 shows the frequency of kana letters in the test sets. The sentence sets were presented to all participants in the same order.

Although the order of sentence sets was the same across participants, its potential impact on the results is considered small because 1) the experimental conditions were counterbalanced across participants, which reduces set-specific effects, and 2) each sentence set has an equal number of letters and comparable vocabulary complexity, which contributes to consistent difficulty across sentence sets.

4.6 Procedure and Task

Participants sat in a chair in front of a desk in a room at our university. We provided details of the task, obtained informed consent from participants, and then asked them to complete a pre-study questionnaire. Next, participants were instructed to: 1) rest their non-dominant hand, which wore a smartwatch, on the desk during the task; 2) touch the smartwatch touchscreen with the index finger of their dominant hand; 3) avoid touching the top bezel for long periods to prevent triggering the OS's standard notification center; and 4) enter sentences as quickly and accurately as possible. In addition, we recommended that they grip the smartwatch with the thumb and middle finger of their dominant hand to increase stability. After these instructions, participants wore the smartwatch on their non-dominant hand.

The task was to transcribe the presented sentences using *Method*. The sentence and the participants' input were displayed above the keyboard feedback on the external display in *Indirect* (Figure 6a) or above the smartwatch keyboard in *Direct* (Figure 6b). The external display was connected to the laptop PC and positioned 0.6 m away from participants (Figure 5). Thus, the visual angle of keyboard feedback was $7.44° \times 8.86°$. Once they determined that they had completed transcribing a sentence, they rotated the smartwatch crown. After this action, the sentence disappeared and the next sentence appeared. The sequence was repeated until all sentences were entered.

In each session, participants first entered 12 sentences for practice and then entered 28 sentences for data collection. After completing a session, they answered questionnaires for the condition, which were the System Usability Scale (SUS) [28], the NASA Raw Task Load Index (NASA-RTLX) [19, 20], and feedback on using *Method*. Participants were required to take a break of at least two minutes between sessions to avoid fatigue. After completing all sessions, participants were asked to complete a post-study questionnaire, which asked their preferred *Method* for each *Touch* condition and the reasons for their preferences.

4.7 Evaluation Metrics and Analysis Methods

We evaluated each *Method* with four metrics:

Text entry speed Characters Per Minute (CPM)
Error rate Total Error Rate (TER) [7]
Usability System Usability Scale (SUS)
Task load NASA Raw Task Load Index (NASA-RTLX)

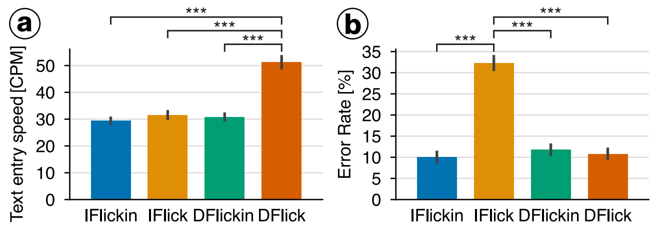

Figure 9: Text entry speed and error rate for each *Touch* × *Method*. Statistical significance: *** p<.001. Error bars represent the 95% confidence intervals.

We used CPM as the metric for text entry speed, as it is commonly used instead of Words Per Minute in Japanese text entry research [4–6, 13, 63]. For error rate, we used TER as it reflects both user mistakes and corrections, providing more insight into the behaviors of the participants [7]. A text entry speed and error rate were measured for each sentence entry; SUS and NASA-RTLX scores were collected for each combination of *Touch* and *Method*. Regarding text entry speed and error rate, we found that they did not follow a normal distribution. Additionally, we treated the SUS scores and NASA-RTLX scores as nonparametric datasets since Likert scale scores are ordinal. Therefore, we applied a nonparametric aligned rank transformation (ART) [22, 56, 69] to these datasets, followed by a two-way repeated measures ANOVA with *Touch* and *Method* as factors. Subsequently, we performed ART-C [11] with Holm correction [23] as a post-hoc analysis.

4.8 Results

We defined the abbreviations of each condition as follows: *Indirect & Flickin* as *IFlickin*, *Indirect & Flick* as *IFlick*, *Direct & Flickin* as *DFlickin*, *Direct & Flick* as *DFlick*.

4.8.1 Text Entry Speed.

The text entry speeds are shown in Figure 9a. Those of the four conditions (IFlickin, IFlick, DFlickin, DFlick) in CPM were 29.5 (SD=9.10), 31.4 (SD=13.5), 30.8 (SD=11.1), and 51.2 (SD=20.7), respectively (higher is better). Significant main effects for *Touch* ($F_{1,1314}$=272.75, p<.001, η_p^2=.172) and *Method* ($F_{1,1314}$=284.47, p<.001, η_p^2=.178), as well as a significant interaction effect for *Touch* × *Method* ($F_{1,1314}$=227.03, p<.001, η_p^2=.147), were observed. A post-hoc analysis revealed that the text entry speed of DFlick was significantly faster than the other conditions (p<.001).

4.8.2 Error Rate.

The error rates are shown in Figure 9b. Those of the four conditions (IFlickin, IFlick, DFlickin, DFlick) were 10.0% (SD=11.0%), 32.3% (SD=14.7%), 11.8% (SD=11.6%), and 10.8% (SD=10.9%), respectively (lower is better). Significant main effects for *Touch* ($F_{1,1314}$=293.41, p<.001, η_p^2=.182) and *Method* ($F_{1,1314}$=327.62, p<.001, η_p^2=.200), as well as a significant interaction effect for *Touch* × *Method* ($F_{1,1314}$=382.45, p<.001, η_p^2=.225), were observed. A post-hoc analysis revealed that the error rate of IFlick was significantly higher than the other conditions (p<.001).

The number of corrections per sentence of the four conditions (IFlickin, IFlick, DFlickin, DFlick) were 1.56 (SD=2.16), 6.59 (SD=4.44), 1.87 (SD=2.32), and 1.70 (SD=2.15), respectively. Significant main effects for *Touch* ($F_{1,1314}$=350.38, p<.001, η_p^2=.210) and *Method* ($F_{1,1314}$=376.73, p<.001, η_p^2=.223), as well as a significant interaction effect for *Touch* × *Method* ($F_{1,1314}$=421.63, p<.001, η_p^2=.243), were observed. A post-hoc analysis revealed that the error rate of IFlick was significantly higher than the other conditions (p<.001).

4.8.3 Usability. The SUS scores of the four conditions (IFlickin, IFlick, DFlickin, DFlick) were 70.6 (SD=19.4), 52.7 (SD=20.9), 72.1 (SD=17.8), and 76.0 (SD=16.8), respectively (higher is better). A significant main effect for *Touch* ($F_{1,33}$=7.95, p<.01, η_p^2=.194), as well as a significant interaction effect for *Touch* × *Method* ($F_{1,33}$= 6.85, p<.01, η_p^2=.172), were observed. A post-hoc analysis revealed that the SUS score of IFlick was significantly lower than the other conditions (p<.05).

4.8.4 Task Load. The overall workload scores of the four conditions (IFlickin, IFlick, DFlickin, DFlick) were 37.2 (SD=17.3), 53.1 (SD=10.5), 39.7 (SD=17.7), and 38.8 (SD=12.9), respectively (lower is better). Only a significant interaction effect for *Touch* × *Method* ($F_{1,33}$=8.37, p<.01, η_p^2=.202) was observed. A post-hoc analysis revealed that the overall workload score of IFlick was significantly higher than the other conditions (p<.01).

4.8.5 Preferences. For *Indirect*, 11 participants preferred *Flickin*. Most of them preferred *Flickin* over *Flick* due to its lower error rate (e.g., *"While I often selected the wrong consonant with Flick, such mistakes did not occur with Flickin"* (P3)). Additionally, P6, P11, and P12 positively evaluated *Flickin* for its ability to cancel input. One participant preferred *Flick* because the participant was already familiar with it.

For *Direct*, six participants preferred *Flickin*. P4, P6, and P10 positively evaluated *Flickin*; they noted that it allows for easy selection of the small keys displayed on a smartwatch (e.g., *"I want to know which key I am tapping. With Flick, the keys are hidden by my finger, but with Flickin, I can see the keys"* (P6)). Six preferred *Flick* because they were already familiar with it.

4.9 Summary of Study 1

We compared the typing performance of the baseline (*Flick*) and our method (*Flickin*) in scenarios where an external display was used as the output surface. The results showed that Flick-in achieved a text entry speed equivalent to the Flick method while significantly reducing the error rate under indirect touch conditions. In addition, Flick-in demonstrated significantly better usability and lower workload scores than the Flick method under indirect touch conditions. Therefore, Flick-in enables accurate Japanese text entry using an external display as the output surface.

5 Study 2

We conducted a user study (Study 2) to evaluate the performance of Flick-in in an MR environment. This study investigated whether Flick-in enables stable typing across various postures and whether typing remains effective even with small keyboard feedback in indirect touch typing using an MR environment as the output surface. Additionally, if Flick-in remains effective even with small keyboard feedback, it suggests that Flick-in can be used without significantly obstructing the user's field of view.

In this study, we used the same implementation of Flick-in as in the indirect condition of Study 1. The study took approximately 150 minutes per participant and was conducted with the approval of the ethics review committee of our institute (2024R955).

5.1 Participants

The study involved 12 participants (one female, 11 males; mean age: 22.3 years, SD = 1.1 years; ID: P13–P24) from our university. None had participated in our previous studies, including Study 1 or the pilot experiments. All participants were right-handed. All participants reported using smartphones daily, and four reported using smartwatches daily. Regarding Japanese text entry methods on smartphones, ten reported using the Flick method daily and two reported using a QWERTY keyboard daily. All participants received approximately 17 USD (2525 JPY).

5.2 Apparatus

We used the same smartwatch and laptop PC as in Study 1, along with an HMD (Meta Quest 3). The applications used in the study consisted of a smartwatch application, a PC application, and an HMD application. The smartwatch application was identical to the one used in Study 1. The PC application functioned as a server to connect the smartwatch and the HMD. The HMD application was implemented in Unity Version 6000.0.26f1. The HMD application received touch coordinates and input sentences from the smartwatch application. These applications communicated wirelessly via BLE and WebSocket.

5.3 Design

We employed a within-subjects design with two independent variables: *Posture* (*Sitting*, *Standing*, *Walking*) and *Size* (*Medium*, *Small*).

Posture represents participants' body posture during the task, in which they entered kana sentences using Flick-in (Figure 10a). In *Sitting* condition, participants performed the task while seated, with their arm resting on the desk, as in Study 1. In *Standing* condition, participants performed the task while standing. In *Walking* condition, participants performed the task while walking around in a room (11.2 m × 5.0 m). Participants were instructed to walk at approximately two steps per second, in which no feedback regarding pace was given and walking speed was left to their discretion.

Size represents the size of a key of keyboard feedback, which was determined based on the UI design guidelines for VR [15] (Figure 10b). These guidelines recommend a minimum target size of 64 dmm. Dmm is an angular unit that represents one millimeter at a distance of one meter from the user's viewpoint. In both conditions, the aspect ratio of the keyboard feedback was almost the same as that of the smartwatch keyboard. In *Medium*, the width and height of each key were 68.3 dmm × 64.0 dmm (3.91° × 3.66°). Thus, the total keyboard feedback size was 204.8 dmm × 256.0 dmm (11.69° × 14.59°). In *Small*, the width and height of each key were 25.6 dmm × 24.0 dmm (1.47° × 1.38°). Thus, the total keyboard feedback size was 76.8 dmm × 96.0 dmm (4.40° × 5.50°).

The order of the conditions (combinations of *Posture* and *Size*) was counterbalanced using a Latin square. All participants engaged in six sessions; each corresponded to one condition. In each session, participants performed text entry for 24 sentences. In total, 1,728

Figure 10: Independent variables in Study 2. a) *Posture*. b) *Size*.

data points (3 *Postures* × 2 *Sizes* × 24 sentences × 12 participants) were collected.

5.4 Sentence Sets

We created six kana sentence sets to provide different sentence sets (see the supplemental material) for the six conditions. Each sentence set consists of one set for practice (practice set) and one set for data collection (test set). A practice set consists of ten sentences; a test set consists of 24 sentences (e.g., "はるかぜがふく" (The spring breeze blows) and "じだいはまわる" (Time goes around)). The length of each sentence is between six and eight letters, with an average of seven letters. In each sentence set, sentences of the same length appeared an equal number of times. A test set contains a total of 168 letters. The test sets' correlation coefficient with the Kyoto Corpus was 0.80 (Figure 8). The sentence sets were presented to all participants in the same order.

5.5 Procedure and Task

The procedure before the task and the instructions were identical to those in Study 1. Additionally, participants were instructed to face forward while performing the task. In both *Standing* and *Walking* postures, participants were allowed to position their arms freely. After these instructions, participants wore the smartwatch on their non-dominant wrist and the HMD.

The task was to transcribe the presented sentences using Flick-in. During the task, the sentence and keyboard feedback were displayed in the MR environment. These elements were positioned at the center of the HMD screen and kept fixed relative to the participant's head. The procedure for entering sentences was identical to that in Study 1.

In each session, participants first entered ten sentences for practice and then entered 24 sentences for data collection. After completing one session, they answered questionnaires for the condition, which are SUS, NASA-RTLX, and feedback on the condition. Participants were required to take a break of at least three minutes between sessions to avoid fatigue. After completing all sessions, participants were asked to complete a post-study questionnaire, which asked their preferred *Posture* and *Size* conditions and the reasons for their preferences.

5.6 Evaluation Metrics and Analysis Methods

We used the same evaluation metrics as those used in Study 1 (text entry speed, error rate, usability, and task load). Regarding text entry speed and error rate, we found that they did not follow a normal distribution. Additionally, we treated the SUS scores and NASA-RTLX scores as nonparametric datasets since scores of Likert

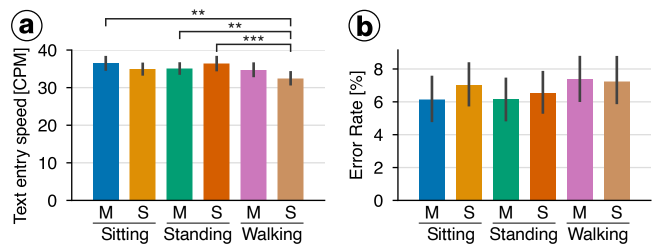

Figure 11: Text entry speed and error rate for each *Posture* × *Size*. Statistical significance: ** p<.01, *** p<.001. Error bars represent the 95% confidence intervals.

scales are ordinal. Therefore, we applied ART to these datasets, followed by a two-way repeated measures ANOVA with *Posture* and *Size* as factors. Subsequently, we performed ART-C with Holm correction as a post-hoc analysis.

5.7 Results

We defined the abbreviations for each condition as follows: *Sitting* & *Medium* as *SitM*, *Sitting* & *Small* as *SitS*, *Standing* & *Medium* as *StandM*, *Standing* & *Small* as *StandS*, *Walking* & *Medium* as *WalkM*, *Walking* & *Small* as *WalkS*.

5.7.1 Text Entry Speed. The text entry speeds are shown in Figure 11a. Those of the six conditions (SitM, SitS, StandM, StandS, WalkM, WalkS) in CPM were 36.5 (SD=14.5), 34.9 (SD=12.1), 35.1 (SD=11.7), 36.4 (SD=14.8), 34.7 (SD=13.9), and 32.4 (SD=13.0), respectively (higher is better). A significant main effect for *Posture* ($F_{2,1666}$=7.87, p<.001, η_p^2=.009) was observed, and no significant interaction effect was observed. A post-hoc analysis showed that the text entry speed of *Walking* was significantly lower than that of *Sitting* (t_{1666}=−3.13, p<.01) and *Standing* (t_{1666}=−3.68, p<.001).

5.7.2 Error Rate. The error rates are shown in Figure 11b. Those of the six conditions (SitM, SitS, StandM, StandS, WalkM, WalkS) were 6.14% (SD=11.0%), 7.02% (SD=11.0%), 6.16% (SD=10.4%), 6.53% (SD=10.8%), 7.37% (SD=11.4%), and 7.23% (SD=11.6%), respectively (lower is better). Only a significant interaction effect for *Posture* × *Size* ($F_{2,1666}$=3.57, p<.05, η_p^2=.004) was observed; however, a post-hoc analysis for *Posture* × *Size* showed that there was no significant difference.

The number of corrections per sentence of the six conditions (SitM, SitS, StandM, StandS, WalkM, WalkS) were 0.606 (SD=1.29), 0.655 (SD=1.19), 0.573 (SD=1.11), 0.627 (SD=1.18), 0.709 (SD=1.32), and 0.713 (SD=1.40), respectively. Only a significant interaction effect for *Posture* × *Size* ($F_{2,1666}$=3.98, p<.05, η_p^2=.005) was observed;

however, a post-hoc analysis for *Posture* × *Size* showed that there was no significant difference.

5.7.3 Usability. The SUS scores of the six conditions (SitM, SitS, StandM, StandS, WalkM, WalkS) were 77.9 (SD=13.5), 76.2 (SD=12.2), 75.4 (SD=13.6), 71.9 (SD=13.4), 68.8 (SD=13.8), and 67.9 (SD=17.5), respectively (higher is better). A significant main effect for *Posture* ($F_{2,55}$=6.06, p<.001, η_p^2=.181) was observed, and no significant interaction effect was observed. A post-hoc analysis showed that the SUS score of *Walking* was significantly lower than that of *Sitting* (t_{55}=−3.45, p<.01).

5.7.4 Task Load. The overall workload scores of the six conditions (SitM, SitS, StandM, StandS, WalkM, WalkS) were 32.6 (SD=17.0), 35.6 (SD=10.2), 37.5 (SD=16.3), 43.1 (SD=17.5), 45.0 (SD=15.2), and 52.2 (SD=14.6), respectively (lower is better). Significant main effects for *Posture* ($F_{2,55}$=15.26, p<.001, η_p^2=.357) and *Size* ($F_{1,55}$=4.48, p<.05, η_p^2=.075) were observed, and no significant interaction effect was observed. A post-hoc analysis showed that the overall workload of *Walking* was significantly higher than that of *Sitting* (t_{55}=5.52, p<.001) and *Standing* (t_{55}=2.93, p<.01). The overall workload of *Standing* was significantly higher than that of *Sitting* (t_{55}=2.59, p<.05). Additionally, the overall workload of *Small* was significantly higher than that of *Medium* (t_{55}=2.12, p<.05).

5.7.5 Preferences. For *Posture*, ten participants preferred *Sitting*. The primary reason for choosing *Sitting* was the stability of the arm wearing the smartwatch. In *Sitting*, participants could rest their hands on the desk; this provides the most stable arm position, which made *Sitting* the most preferred posture. On the other hand, one preferred *Standing* ("Placing the arm imposed a burden on the wrist" (P17)), and one preferred *Walking* ("This method was particularly useful for walking" (P24)).

For *Size*, ten participants preferred *Medium*. The reasons for choosing *Medium* instead of *Small* included better keyboard visibility (P13, P23) and easier text entry (P16, P18–P21). Two participants preferred *Small*. P17 favored it due to the reduced eye movement required.

5.8 Summary of Study 2

We investigated the typing performance of Flick-in, which uses an MR environment as the output surface, as well as the effects of user posture and keyboard feedback size. The results showed that text entry speed, usability scores, and workload scores while walking were significantly lower than those while sitting or standing. In contrast, there was no significant difference in error rates across all conditions, and both text entry speed (32.4–36.5 CPM) and error rates (6.14–7.37%) remained stable within a narrow range. Therefore, Flick-in realizes accurate indirect touch typing even when an MR environment is used as the output surface and demonstrates stable typing performance even while walking or when the keyboard feedback size is small.

6 Discussion

In this section, we discuss the typing performance, keyboard feedback design, and applicability of Flick-in. Additionally, we examine the limitations of this study.

6.1 Typing Performance of Flick-in

The results of Study 1 and Study 2 demonstrate that Flick-in enables accurate Japanese indirect touch typing in scenarios where an external display or an MR environment is used as the output surface, across various postures. These findings suggest that Flick-in is an effective and robust method for Japanese indirect touch typing and can be applied in various situations.

In Study 2, while the text entry speed of Flick-in was significantly lower while walking than sitting or standing, the error rate did not increase significantly, and the effect sizes for both text entry speed and error rate were small (η_p^2=0.009 and η_p^2=0.001 for text entry speed and error rate, respectively). Previous studies have shown that pointing and touch accuracy, including flick gestures, while walking is lower than while standing or sitting [13, 38, 59]. In contrast, Flick-in maintained stable performance even while walking. This stability is likely due to the use of touch-up gestures, which is consistent with previous work that employed touch-up gestures for English text entry [1, 27, 30, 68]. Therefore, our study extends their findings to Japanese text entry and MR environments. Additionally, we observed that all participants operated the smartwatch with their arms placed on their abdomen, and several (P13, P15–18, P20) mentioned that they experienced no difficulties in typing with this posture. This suggests that Flick-in allows users to place their arm wearing the smartwatch in a favorite position, which likely contributed to stabilizing the smartwatch and minimizing the decline in input performance while walking.

However, Flick-in is not the optimal typing method for all situations. In direct touch scenarios, Flick-in showed a significantly lower text entry speed than the Flick method. Moreover, the text entry speed of Flick-in was slower than that of existing Japanese text entry methods for smartwatches, such as SliT [5] (50 CPM after 30 days) and PonDeFlick [4] (57.7 CPM after 10 days). This would be due mainly to the design of Flick-in for consonant selection to realize accurate kana text entry in indirect touch scenarios. These methods allow users to select a consonant quickly while visually confirming. In contrast, Flick-in requires users to carefully move the pointer to the target position through a slide gesture to select a consonant. This design makes Flick-in inherently slower due to the need for precise pointing to small targets. Thus, these methods are more suitable than Flick-in in direct touch scenarios.

6.2 Keyboard Feedback of Flick-in

The results of Study 2 showed no significant decline in text entry speed, error rate, or usability, even when using a small keyboard feedback size. This suggests that Flick-in remains practical even with small keyboard feedback. Participants noted that smaller keyboard feedback offers advantages such as improved visibility of the surrounding area (P14, P16, P19) and reduced eye movement (P19, P23, P24). These results show that Flick-in functions with the small keyboard feedback, thereby lowering the degree to which it occupies the user's field of view, and suggest that Flick-in can also be used on small output surfaces (e.g., augmented reality glasses). In contrast, many participants preferred larger keyboard feedback and expressed concerns about the negative effects of smaller feedback, such as eye strain. Therefore, the keyboard feedback size should be adjusted according to the specific usage scenario.

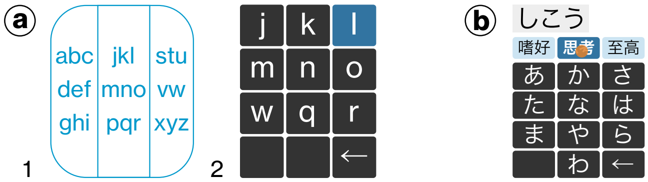

Figure 12: Extensions of Flick-in. a) Application of Flick-in to English text entry based on the GAT3 keyboard [2]. Users select an alphabet group by performing a touch-down gesture or a BIS. b) Flick-in with kana-kanji conversion function. Users select one of kanji candidates via a pointer.

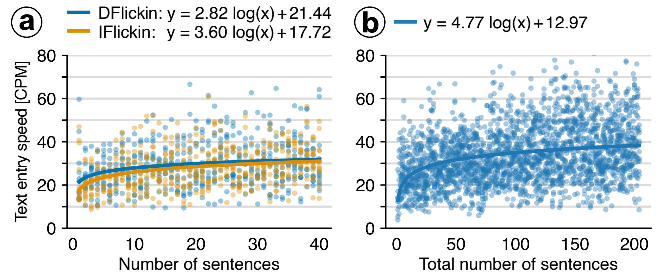

Figure 13: Transition of text entry speeds and their fitting curves over the practice and data collection. a) Result of Study 1 for both IFlickin and DFlickin. b) Result of Study 2.

The keyboard feedback of Flick-in could be simplified to minimize obstruction of the user's view. In Study 2, several participants mentioned that the keyboard placed at the center obstructed their view and felt uncomfortable (P16, P17). Thus, it is necessary to explore the performance and usability of Flick-in by redesigning the keyboard feedback, such as by increasing its transparency. Furthermore, future work could involve testing grid-only keyboard feedback. This would allow users to enter text once they have memorized the keyboard layout.

6.3 Applicability of Flick-in

Although we designed and tested Flick-in for a rectangular smartwatch as the input surface, it can also be applied to input surfaces of other shapes. For a circular smartwatch, the accuracy of eyes-free BIS in six directions was 93.34% [70], which suggests that Flick-in could realize accurate text entry on a circular smartwatch as the input surface. In addition, Flick-in could be used with input surfaces that allow users to slide in an accurate direction without looking at the input surface (e.g., smartphones, controllers with touchpads). Further studies are needed to investigate the applicability of Flick-in to various input surfaces.

Flick-in has the potential to be applied to other languages. We designed Flick-in to first select a vowel, then choose a target kana letter that shares the selected vowel. In other words, users first select one of several character groups and then choose a character within the group. Thus, Flick-in could be adapted for other languages if their characters can be classified into distinct groups, such as in Korean [25]. For example, by dividing the alphabet into multiple groups, Flick-in can support English text entry, as suggested by previous studies [2, 10] and as shown in Figure 12a. The design shown allows for larger key sizes than those on the QWERTY keyboards on smaller input surfaces.

6.4 Limitations

Our research has several limitations. First, this study did not examine the long-term stability of Flick-in. In Study 2, participants entered more sentences than in Study 1, resulting in a higher average CPM, as shown in the fitting curves of Figure 13. This result suggests that CPM could improve as users become more proficient with Flick-in. In this paper, we focused on conducting a short-term evaluation of the basic performance and practicality of Flick-in in an MR environment. However, we acknowledge the importance of longitudinal studies and plan to explore this in future work to better understand its performance in daily use.

Second, a kana-kanji conversion function has not been addressed although it is essential for Japanese text entry. Flick-in can incorporate a conversion function that displays conversion candidates on the output surface, allowing users to select the desired kanji via a touch-up gesture with the design illustrated in Figure 12b. Our immediate future work is to implement this kana-kanji conversion function and evaluate its typing performance.

Finally, the design of Flick-in used in this study may not be optimal. To improve learnability, we aligned the bezels corresponding to vowels with the arrangement of vowel keys in the Flick method. However, in this design, the direction of finger movement for vowels is opposite to that of the Flick method. Several participants reported confusion due to this discrepancy (P1, P8, P12, P23), while others noted that their confusion diminished with practice (P16, P18, P19, P20, P22). Furthermore, input cancellation posed challenges. Some participants noted that the cancellation area was too small (P13, P18) and wanted to cancel even after selecting the 'a' vowel (P21, P22). In contrast, P22 canceled input by selecting blank keys when the vowel was 'i' or 'e' (Figure 4c), which are the keys in the second column from the left and the third row from the top in the consonant key arrangement for the 'i' or 'e' vowels. This suggests a potential solution: adopting a 4×4 keyboard layout with a dedicated cancellation key to improve discoverability and usability. Consequently, further research is needed to explore the optimal design.

7 Conclusion

In this paper, we presented Flick-in, a Japanese text entry method for indirect touch using BIS on smartwatches. We first evaluated the performance of Flick-in with an external display as the output surface. The results showed that Flick-in achieved a text entry speed of 29.5 CPM with an error rate of 10.0%, which was a lower error rate than that of the Flick method. Subsequently, we evaluated the performance of Flick-in in an MR environment across various postures and keyboard sizes. The results showed a text entry speed of 36.5 CPM with an error rate of 6.14%. Furthermore, participants were able to operate Flick-in effectively even when the keyboard feedback size was reduced. These results show that Flick-in is suitable for indirect touch typing in Japanese.

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