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PAPER

Gesture-Based Smartwatch Text Entry: Design, Evaluation, and Future Applications

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ABSTRACT

This work presents an approach for text entry on smartwatches through continuous gesture recognition of geometric shapes. The method allows users to input characters using simple and easily reproducible gestures, such as straight lines and curves, which are recognized in real time as they are performed. A Naïve Bayes classifier categorizes gestures into letters based on conditional probability, and a trie data structure stores words together with their corresponding usage probabilities to enable word suggestion generation during input. The system also incorporates a mechanism that considers both shorter and more frequent words by balancing word length and usage probability. A user evaluation assessed perceived usability using the System Usability Scale (SUS), resulting in an average score of 92.5, which reflects a strong perception of ease of use, low complexity, and rapid learnability. In addition, a quantitative performance analysis indicated an average entry speed of 16.0 words per minute (WPM), providing a complementary characterization of the user interaction behavior. Together, these results indicate that the method provides a feasible interaction approach for devices with limited input space and offers a solid foundation for future studies exploring its applicability in wearable computing, accessibility, and educational contexts.

KEYWORDS

smartwatch, text entry, continuous gesture recognition, interaction

1 INTRODUCTION

The use of wearable devices, along with ongoing technological advancements, brings us closer to the concept of ubiquitous computing proposed by Weiser [1]. The increasing integration of wearable technologies into daily life has expanded their use across both personal and professional domains, supporting applications in health monitoring, communication, and mobile learning [2], [3]. Among these devices, the smartwatch has gained particular relevance due to its portability and ease of access. Its adoption continues to grow [4], [5], enabling users to perform everyday tasks such as replying to messages and controlling connected devices.

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Consequently, it is essential to develop interaction methods that are both efficient and responsive for these devices.

Beyond personal convenience, wearable technologies have also demonstrated growing potential in educational and assistive contexts, where they can promote engagement, accessibility, and adaptive learning experiences [2], [6]. Recent discussions on digital innovation in education further emphasize how emerging information and communication technologies (ICT) tools contribute to more adaptive and transformative learning environments [7]. These developments underscore the need for interaction methods that are efficient and flexible enough to support inclusive, context-aware applications.

Despite the extensive research on smartwatch text input, the limited screen size of these devices continues to pose significant challenges. Interaction remains difficult, even though these devices were originally intended to simplify user tasks. Therefore, it is important to design interaction techniques that are both efficient and adaptable, with text input methods playing a central role in this process [8]–[11]. Similar difficulties have been observed in smartwatch text entry research, where existing methods often involve a trade-off between accuracy and input speed [12].

Gesture-based interaction has been extensively studied in wearable computing as an alternative interaction technique for devices with restricted display areas, demonstrating its potential to improve input efficiency and reduce errors [13], [14]. In a previous work [11], we proposed a method that employs continuous gesture recognition combined with a Naïve Bayes classifier for character entry on smartwatches, using simple geometric shapes such as lines and curves. Based on these gestures, users can form words and sentences through a dictionary that provides possible word completions based on the entered characters.

The primary objective of this work is to develop a method that enables text input on smartwatches through continuous gesture recognition, thereby bypassing character-by-character input. In the proposed approach, users perform a single gesture corresponding to each character, while the system continuously recognizes these gestures and maps them to letters. Recognized inputs are then used to predict words and sentences. The method integrates a gesture recognition algorithm, a Naïve Bayes classifier for letter inference, and a trie-based dictionary that stores words along with their relative usage probabilities to support word prediction.

The main contribution of this work is a gesture-based text input method for smartwatches that enables users to enter complete words through continuous gesture recognition and probabilistic word prediction, reducing the need for explicit discrete character input. This approach is designed to support more fluid and natural interaction on devices with limited screen space. The remainder of this paper is structured as follows: Section 2 reviews related work; Section 3 presents the proposed method; Section 4 describes the experimental procedure; Section 5 discusses the results, and Section 6 concludes the paper.

2 RELATED WORK

Various text entry techniques have been proposed to address the interaction constraints of smartwatches and other wearable devices. Previous research has explored solutions based on miniature keyboards, touch and swipe interactions, crown-based controls, and gesture recognition. Some of these approaches are reviewed in the following paragraphs, highlighting representative solutions in this study area.

The work proposed by Gong et al. [15] introduced *WrisText*, a method that enables text entry on smartwatches using a single hand, relying on wrist movements that resemble joystick-like interaction. Cha et al. [16] proposed *Virtual Sliding QWERTY (VSQ)*, which employs a virtual QWERTY layout and a *Tap-N-Drag* mechanism to dynamically reposition the keyboard. Wong et al. [17] developed *FingerT9*, which maps a T9 layout to finger segments, allowing text input through thumb-to-finger interaction detected via embedded sensors.

Oney et al. [18] presented *Zoomboard*, which allows users to tap on letter regions that expand to enable a more precise selection. Darbar et al. [19] proposed the *ETAO Keyboard,* which displays the most frequent English letters on the main screen for single-tap input, with double-tap access to numbers and symbols. Kominos and Dunlop [20] divided the smartwatch screen into seven input zones, enabling text entry through taps and swipe gestures for backspacing and word completion.

WearWrite, developed by Nebeling et al. [10], is a collaborative writing application that enables smartwatch users to send and receive notifications directly on the device. Gordon et al. [21] designed *WatchWriter*, a keyboard that supports both touch and gesture typing through statistical decoding. Hong et al. [22] introduced a swipe-based QWERTY keyboard that allows users to alternate between keyboard halves with horizontal swipes. Mäkelä et al. [23] proposed *HideWrite*, which allows users to draw text on a dimmed smartwatch display in order to preserve privacy during input.

Rakhmetulla and Arif [12] developed *Crownboard*, a method for users with limited dexterity that combines crown-based zone selection and word prediction to enhance speed and accuracy. Akamine et al. [24] introduced *PonDeFlick*, a Japanese smartwatch text entry method that aligns flick directions with smartphone layouts, improving input efficiency as demonstrated in a ten-day user study. Lai et al. [25] proposed *Tap'nSwipe*, which divides the screen into nine-character regions and integrates word prediction to increase accuracy and usability compared to standard QWERTY layouts.

More recently, Liu et al. [13] introduced *CrossKeys*, a virtual reality text entry system that used one-handed wrist rotation for spatial character selection, achieving high input speed and low error rates. Li et al. [14] proposed *FineType*, a tapping gesture–based system that recognizes fine finger combinations and postures on flat surfaces, achieving high typing accuracy and speed through a wrist-mounted sensing mechanism.

Miao et al. [26] presented *GazePinch*, which combines gaze tracking and pinch gestures for word-level text entry in mixed reality, thereby reducing fatigue and improving comfort during extended use. Banerjee et al. [27] developed *ThumbSwype*, a thumb-to-finger gesture input method for head-mounted displays that overlays a virtual QWERTY keyboard on the user's fingers, enabling one-handed swipe typing with enhanced comfort. Lamsellak et al. [28] proposed a multi-sensor learning framework for gesture recognition using accelerometers and gyroscopes, demonstrating effective performance in both educational and assistive contexts.

Gesture recognition on mobile and wearable devices has also been investigated as a means to enable new interaction paradigms. Magrouni et al. [29] explored real-time recognition of hand and fingertip movements for command execution, highlighting precision and robustness. Lin et al. [30] proposed a contactless gesture recognition system for wrist-worn devices based on inductive proximity sensing, which captures muscle activity without direct contact, improving comfort and usability. Similarly, AI-driven systems have been designed to interpret gestures and speech, expanding the potential for multimodal interaction in wearable interfaces [31]. Fallah and MacKenzie [32] introduced *LeapBoard*, a multimodal interface that combines mid-air gestures with a physical keyboard to improve interaction efficiency and reduce fatigue. Papadakis et al. [33] highlighted the role of emerging AI-enhanced ICT interaction paradigms in supporting adaptive and user-centered learning environments.

Moreover, users have shown positive responses to continuous gesture recognition techniques on smartwatches, as reported by Nascimento et al. [34]–[36]. In our previous work [11], we proposed a gesture-based text input method that uses geometric shapes for character entry, allowing each letter to be entered with at most two interactions and supporting word formation through a dictionary-based predictive mechanism.

Therefore, this work aims to present a text input method that enables users to enter words and sentences by performing only the initial gesture associated with each character, supported by a predictive dictionary. This approach reduces the need for explicit letter-by-letter tracing and is designed to preserve input accuracy. A user evaluation was conducted to assess both the usability and the performance of the system. The primary contribution of this work is a gesture-based text input method that minimizes interaction effort while maintaining accuracy through predictive word suggestions.

3 METHOD DETAILS

We developed a method that enables users to input text on smartwatches through a set of simple gestures based on geometric shapes. Characters are entered using a predefined set of gestures composed of straight lines and curves, previously validated in an earlier study [35]. Each gesture corresponds to a letter, allowing users to perform text entry through a single continuous gesture for each character. The proposed method combines a continuous gesture recognition algorithm, a Naïve Bayes classifier, and a trie data structure to support gesture recognition and word prediction. Figure 1 illustrates the overall structure of the proposed method and the interactions between its main components.

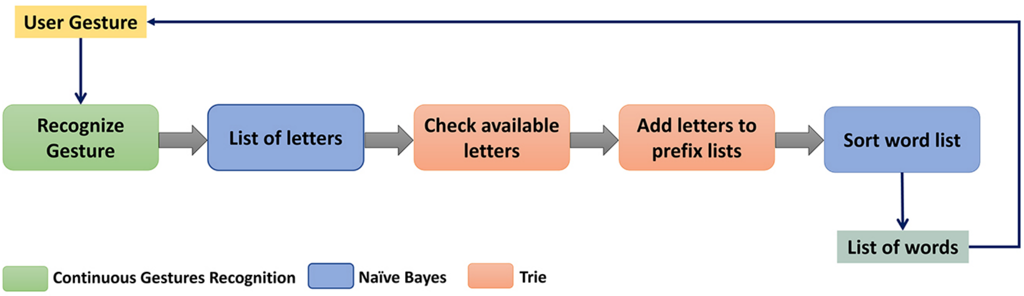

Fig. 1. Structure of the method developed for text entry

As shown in Figure 1, to compose a word, the user performs a single gesture for each letter, corresponding to the initial stroke of that character. However, because the method can recognize words from partial letter sequences, some words can be inserted with fewer gestures than the number of letters they contain. The gesture set includes basic geometric forms such as vertical and horizontal lines, diagonal strokes, circles, and semicircles, as illustrated in Figure 2.

Fig. 2. Set of gestures used to enter letters

After each gesture, the system updates a list of candidate prefixes corresponding to the letters identified by the Naïve Bayes classifier. Next, a search is performed in the word dictionary to determine which prefixes are valid based on the input sequence. Invalid prefixes are discarded, and the most probable word is presented to the user, who can then:

- Confirm the selection of the suggested word;
- Select an alternative word from the list of candidates;
- Perform an additional gesture, repeating the process illustrated in Figure 1; and
- Wait two seconds for the system to automatically confirm the current prediction.

To support error recovery, the method includes specific editing gestures. A leftward swipe performed over the text field acts as a backspace, removing the last recognized gesture. Additionally, a long press on the screen deletes the entire word currently being composed, allowing the user to quickly reset the input sequence.

A prototype implementing the procedure illustrated in Figure 1 was developed. Figure 3 presents the prototype interface and illustrates the step-by-step process of entering the phrase *THANK YOU*, demonstrating how gestures are translated into text on the smartwatch screen.

Fig. 3. Prototype being used to enter the text *THANK YOU*

By employing the continuous gesture recognition algorithm, the user does not need to finish the gesture or lift the finger from the screen for recognition to occur. Once a gesture is recognized, the system displays the candidate words associated with the detected letters and their corresponding prefixes. To provide visual feedback indicating successful recognition, the color of the ongoing gesture changes from black to red. Figure 4 illustrates this process during the input of the letter *K* in the word *THANK*. This visual feedback is provided for each letter.

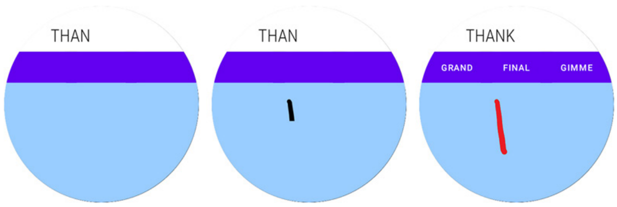

Fig. 4. Example of gesture in progress highlighted in red after recognition

To complement the description and demonstrate the practical operation of the proposed method, a demonstration video is available at: https://doi.org/10.6084/m9.figshare.29923760. The video illustrates the continuous gesture recognition process, showing how each stroke is mapped to a letter and how word suggestions are dynamically updated in real time during input. It also highlights visual feedback mechanisms, such as gesture color changes and the dynamic update of candidate words. As demonstrated, some words can be completed with fewer gestures than their total number of letters due to the system's ability to anticipate the intended word while the input is still in progress.

3.1 Continuous gesture recognition

The continuous gesture recognition algorithm plays a central role in enabling fluid interaction on smartwatches by identifying gestures in real time. Proposed by Kristensson and Denby [37], this algorithm predicts incomplete gestures, allowing recognition to occur before the movement is fully performed. This capability ensures faster system response and enhances overall interaction fluidity. In the developed prototype, a minimum extension of 2 cm was defined as the activation threshold to ensure gesture distinctiveness without requiring large or tiring movements from the user.

In this approach, each gesture is modeled individually and progressively segmented to allow incremental pattern description. Each segment corresponds to a portion of the overall gesture, enabling the system to interpret actions as the movement unfolds. This hierarchical recognition structure improves responsiveness by anticipating the user's intended input. Figure 5 illustrates the segmentation process, showing how the gesture is decomposed into sequential segments that support early and accurate recognition.

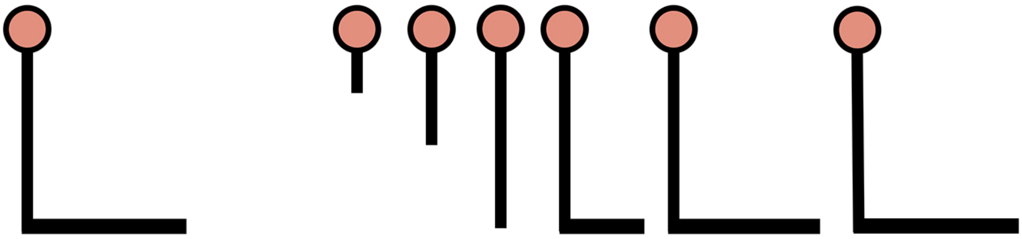

Fig. 5. Complete gesture model on the left and its segmented representations on the right (Adapted from [37])

The segmentation technique offers significant advantages for the continuous gesture recognition process, as it allows the algorithm to begin analyzing and comparing gesture patterns even before the gesture is fully completed, making the interaction faster and more responsive. This approach aligns with the methodology here adopted, contributing to a smoother interaction experience. In Figure 5, the start of the gesture is represented by a circle. The left side of the figure shows the complete gesture model, whereas the right side presents its partial segments. A model is represented by an ordered vector of points that describes the expected sequence of movements. For segmentation, the gesture is divided into progressively growing parts, allowing for incremental and more accurate analysis. The representation of a model is denoted as $w = l, S$, where l describes the complete model and S is the set of segments defined in temporal order T, as shown in the following formula [37]:

$$S = [s_1, s_2, \ldots, s_n]^t,$$

where, s_1, s_2, …, s_n represent the individual gesture segments, and n denotes the total number of segments that compose the complete gesture.

The continuous recognition algorithm treats each gesture as a pattern to be identified by calculating the probability of correspondence between the ongoing gesture and the stored models. To optimize processing time, the multithreading parallelization technique proposed by Nascimento et al. [35] is applied, enabling simultaneous comparison of n gestures, where n corresponds to the number of threads supported in parallel by the smartwatch. This approach improves real-time recognition performance and helps ensure responsiveness during continuous interaction.

3.2 Naïve Bayes classifier

The Naïve Bayes classifier plays a central role in the proposed method, as it is responsible for identifying the possible letters and words to be inserted based on the gestures performed by users. In the classification context, this algorithm relies on the concept of conditional probability and assumes conditional independence among the attributes, which enables efficient learning even with relatively small training data [38]. The classifier assigns each input to a class by calculating the posterior probability of membership, given the observed features. This process is governed by Bayes' Theorem, expressed as follows:

$$P(C_k \vee x) = \frac{P(C_k)\,p(x \vee C_k)}{P(x)}.$$

In this context, each word is modeled as a class. As gestures are performed, the corresponding letters are progressively added to a list of prefixes that represent candidate word constructions. The application of probabilistic modeling based on Bayes' Theorem in the Naïve Bayes classifier enables the estimation of the probability associated with the insertion of a given word, as expressed in the following formula:

$$P(C_k | g_1, g_2, \ldots, g_n) = P(C_k) \prod_{i=1}^{n} P(g_i | L_i).$$

Here, n denotes the number of gestures performed by the user. The probability that each gesture corresponds to a specific letter is computed as follows:

$$P(g | L_i) = \frac{P(g)P(L_i | g)}{P(L_i)}.$$

To estimate the probability of a gesture being associated with a specific letter, a dataset collected from 30 participants was used, in which participants drew all the letters of the alphabet using the gestures illustrated in Figure 2. The dataset allowed the identification and quantification of the different ways in which each letter can be initiated, supporting a statistical analysis of users' gesture preferences and their frequencies of occurrence.

3.3 Word dictionary and classification

We employed a dictionary comprising the 1000 most frequent words in the English language, each associated with its relative frequency of use. Thus, this structure can be readily adapted to other languages by adjusting the base dictionary. The words are organized in a trie data structure, where each word is represented by a terminal node corresponding to its final character, together with the sequence of its ancestor nodes. This hierarchical representation supports structured vocabulary encoding and enables rapid word retrieval within the model.

The terminal nodes, corresponding to the final character of each word, are essential for constructing and identifying words within the trie. This compact structure supports the storage of a large vocabulary, including morphological variations and word extensions such as *smart*, *smartwatch*, and *smartwatches*, thereby enhancing the generation of relevant word suggestions during text entry. Additionally, the flexible dictionary design permits the inclusion of abbreviations and commonly used expressions in short messages, improving usability in contexts such as text input on mobile or wearable devices.

Figure 6 illustrates examples of stored words, including *and*, *any*, *end*, *enter*, *entry*, *entered*, *ten*, *test*, *text*, *wear*, *wearable*, *smart*, and *smartwatch*. The diversity of words stored in the trie structure allows the method to offer a wide range of candidate words and suggestions during text input.

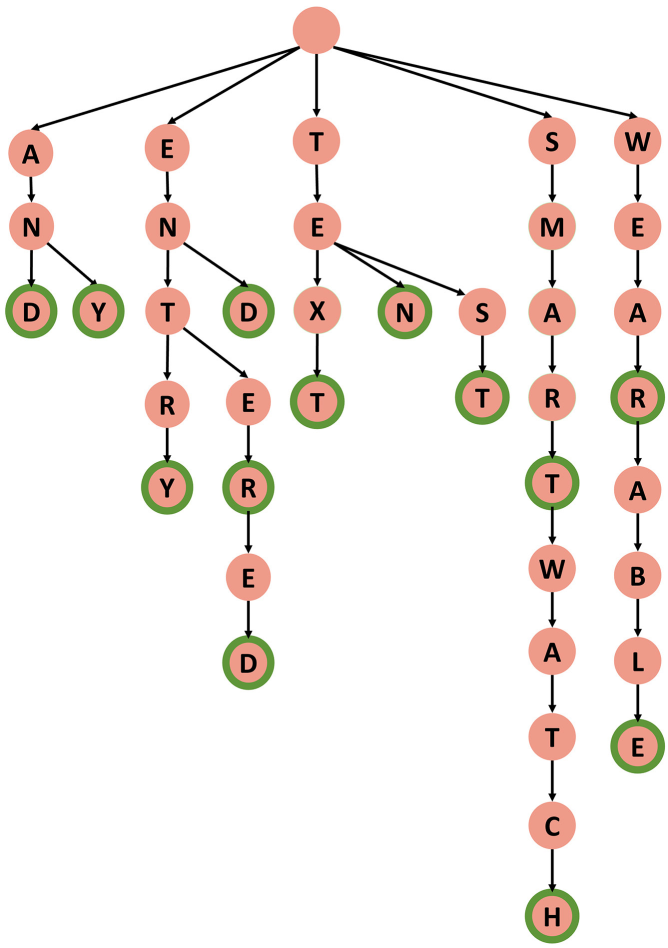

Fig. 6. Trie structure illustrating word storage and retrieval for predictive text input

To improve suggestion accuracy, we integrate the relative probability of word usage with the prioritization of shorter words. Short words, although useful, often exhibit lower usage probabilities and might otherwise be underrepresented if frequency were the sole criterion. By balancing these two factors, the system provides suggestions that are both frequent and concise, supporting interaction in scenarios where input time or space is limited.

4 EXPERIMENT

We conducted an exploratory study with ten volunteer participants, aged between 19 and 56 years, to evaluate the proposed method. Among them, seven did not own a smartwatch, while three reported regular use. Regarding prior experience with wearable technologies, five participants were beginners, two had limited experience, and three were experienced users. All participants wore the smartwatch on their left wrist. According to Virzi [39], as few as four participants are sufficient to identify most usability issues, and Nielsen [41] similarly emphasizes that small groups are capable of uncovering the main interaction challenges. Consistent with the findings of Tullis and Stetson [42], usability studies with small samples, typically involving between eight and twelve participants, can still provide reliable and consistent results when the SUS is applied systematically. Accordingly, this study is exploratory in nature and aims to provide initial indications of usability and performance.

During the experiment, participants were asked to use the proposed method to input commonly used phrases for mobile text input. Ten phrases were selected from the set proposed by Vertanen and Kristensson [43], as listed in Table 1. Task completion time was recorded from the moment the participant initiated the first gesture until the final confirmation of the last word. After completing the tasks, participants evaluated the system using the System Usability Scale (SUS) questionnaire. It should be noted that the method does not support punctuation input; therefore, participants entered only words, without graphical symbols.

Table 1. Sentences used in the experiment

Are you going to join us for lunch?
Are you in today?
Do you need it today?
How are you?
I am on my way.
I am walking in now.
Is it over?
OK with me.
See you soon!
Yes, I am playing.

The recorded interaction data were used to compute standard quantitative performance metrics commonly adopted in text entry research. Entry speed was measured as words per minute (WPM), following the definition established by MacKenzie and Soukoreff [44] and applied by Vertanen and Kristensson [43], assuming a standardized word length of five characters, including spaces. Accuracy was assessed using the total error rate (TER) and the uncorrected word error rate (WER), according to the unified error metric framework proposed by MacKenzie and Soukoreff [44]. Interaction cost was quantified using gesture count per character (GCPC), an adaptation of the keystrokes per character (KSPC) metric [44], calculated as the ratio between the total number of executed gestures and the number of characters in the final transcribed text.

For the experiment, the proposed method was installed on a *Fossil Gen 4* smartwatch with the following specifications: a 1.4-inch circular display, a resolution of 454 × 454 pixels, 512 MB of RAM, and a 1.2 GHz Snapdragon 2100 processor (ARM Cortex-A7 quad-core). Direct interaction with the system by participants enabled an assessment of its perceived usability, providing insights that can guide future refinements.

4.1 SUS

The SUS is one of the most widely adopted instruments for assessing the usability of interactive systems. It comprises ten statements that alternate between positive and negative items, rated on a five-point Likert scale. The final score is calculated through normalization: for odd-numbered (positive) items, 1 is subtracted from the assigned score, while for even-numbered (negative) items, the assigned score is subtracted from 5. The total sum is then multiplied by 2.5, resulting in a score ranging from 0 to 100.

This methodology was applied to compute the usability score of the developed system. Table 2 presents the statements adapted to the context of the proposed application, preserving the original structure recommended by Brooke [45], [46]. According to established guidelines, scores above 68 indicate good usability and serve as a reference for interpreting the obtained results [40].

Table 2. Usability questionnaire (Adapted from [45])

Q1	I would use this system to perform text entry on smartwatches in my daily life.	↑
Q2	I find the system unnecessarily complex.	↓
Q3	I found the system intuitive and easy to use.	↑
Q4	I think I would need the help of a person with technical knowledge to use the system.	↓
Q5	I think the various functions of the system are very well integrated.	↑
Q6	I think the system has a lot of inconsistency.	↓
Q7	I imagine people will learn to use this system quickly.	↑
Q8	I found the system very complicated to use.	↓
Q9	I felt confident using the system.	↑
Q10	I needed to learn several things before using the system.	↓

The application of the SUS enables the identification of critical usability issues and facilitates the comparison of users' experiences with similar systems. The alternation between positive and negative statements helps minimize response bias, promoting a more balanced and reliable evaluation. Therefore, the SUS represents an effective and low-cost instrument for quantitatively assessing users' perceived ease of use of the proposed system.

4.2 Ethical statement

This study adheres strictly to ethical principles in research involving human participants. All participants who took part in the study did so entirely on a voluntary basis, having been fully informed about the objectives, procedures, and nature of the research. Prior to the beginning of the experiment and data collection, each participant read and signed an informed consent form. Participants were informed that they could withdraw from the study at any time, without providing any justification and without facing any negative consequences. No monetary compensation or financial incentive was offered for participation.

Throughout the study, strict ethical standards regarding confidentiality and anonymity were maintained. No personally identifiable information was collected or stored, and all data used in the analysis were reported in aggregated form. The authors affirm that no conflicts of interest exist in the conduct of this study or its reporting, ensuring the integrity and objectivity of the research. These measures collectively underscore the study's commitment to upholding the highest ethical standards in research.

5 RESULTS AND DISCUSSION

We present the results of the user evaluation conducted with the proposed method. The analysis is organized into quantitative performance metrics, a perceived usability assessment, and a subsequent discussion that relates these findings to the characteristics of text entry on smartwatches. Together, these results describe the observed interaction behavior and users' perceptions within the scope of the evaluation performed.

5.1 Quantitative performance

The experiment enabled the collection of quantitative metrics related to the method's behavior during text entry. These metrics provide an objective characterization of the interaction, encompassing entry speed, error rates, and gestural interaction cost. Table 3 summarizes the main quantitative indicators obtained in the experiment, including WPM, TER, GCPC, and WER. These values were computed from the interaction data and the final transcriptions produced by participants during the execution of the text entry tasks.

Table 3. Quantitative text entry metrics

Metric	Mean	SD
WPM	16.0	4.5
TER (%)	6.5	3.2
GCPC	0.80	0.10
WER (%)	0.0	–

The analysis of entry speed revealed an average of 16.0 WPM (SD = 4.5). This result indicates that the method enabled an entry rate comparable to gestural approaches and smartwatch text entry techniques reported in the literature, considering the inherent constraints of screen size and the continuous nature of the interaction. Regarding accuracy, the TER was 6.5% (SD = 3.2). Notably, participants successfully noticed and corrected these errors during the entry process, resulting in final transcripts with no incorrect words and a WER of 0%.

Gestural interaction cost was analyzed using the GCPC, which presented a mean value of 0.80 (SD = 0.1). This result indicates that, on average, less than one gesture was required per inserted character, suggesting that the prediction mechanism contributed effectively to reducing the number of gestures executed during text entry.

Taken together, these quantitative results describe an interaction pattern characterized by entry speeds compatible with existing methods, controlled error rates, and low average gestural cost per character. These results provide objective evidence regarding the method's behavior during use and establish a complementary basis to the perceived usability evaluation.

5.2 Perceived usability

Complementing the objective performance metrics, the perceived usability was evaluated using the SUS questionnaire. All participants successfully entered the required phrases, performing one gesture per letter, which indicates that the interaction method functioned adequately for the tasks in this evaluation. The average score obtained in the SUS questionnaire was 92.5 (SD = 4.2, 95% CI [89.5, 95.5]), indicating a highly positive perception of the system's usability. The confidence interval reflects the variability expected in a study with a reduced sample size while still supporting a mean score associated with the upper range of SUS-based usability classifications. The internal consistency of the responses, measured using Cronbach's alpha, was 0.88, which demonstrates good reliability according to the standards reported by Sauro and Lewis [40]. As illustrated in Figure 7, the distribution of normalized responses across the SUS items was consistently high across all items.

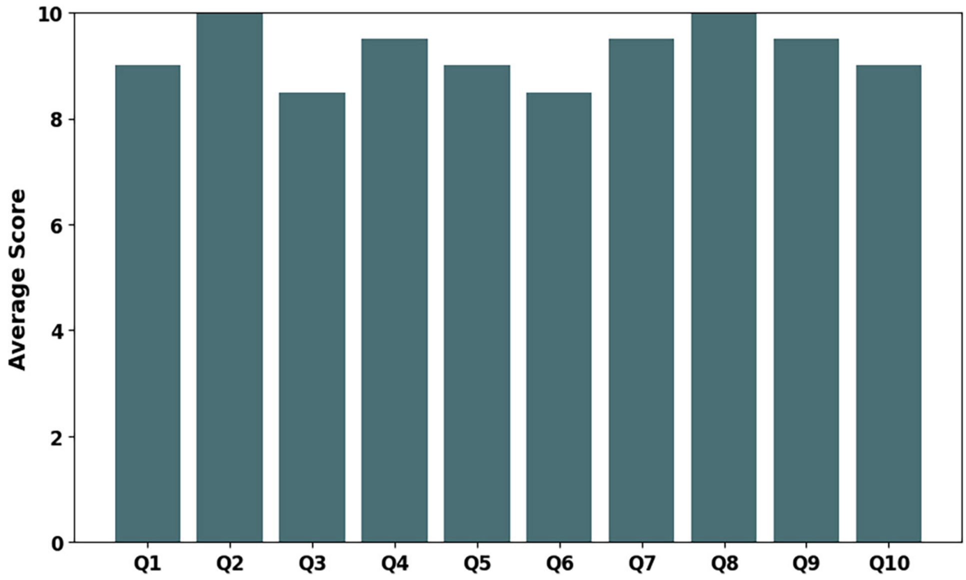

Fig. 7. Normalized average score for each questionnaire item

By applying the normalization procedure for the SUS scale, all positive and negative items were converted into a unified metric in which higher values represent better perceived usability. This transformation ensures interpretive consistency across items of differing polarity and enables a direct comparison of each statement's contribution to the system's overall evaluation, thereby avoiding the ambiguities inherent in the questionnaire's original scoring format.

As shown in Figure 7, the normalized SUS scores reveal a consistent pattern of high evaluations across all dimensions measured by the instrument. Positively worded items, which address willingness for everyday use, intuitiveness, functional integration, rapid learning, and confidence during interaction, received scores between 8.5 and 9.5. These values indicate that participants perceived the system as comprehensible, functionally coherent, easily assimilated, and capable of supporting a stable interaction experience.

The originally negative items, analyzed after normalization that converts disagreement into higher usability values associated with higher usability, obtained scores between 9.0 and 10.0. This result reflects low agreement with perceptions of excessive complexity, the need for technical assistance, structural inconsistency, difficulty of use, and the requirement for prior learning. When considered together, these findings suggest that the interface was perceived as simple, predictable, and cognitively lightweight, attributes that are particularly relevant for devices with highly constrained interaction spaces such as smartwatches.

Although all items exhibited high ratings, the statements evaluating intuitiveness (Q3) and perceived inconsistency (Q6), both scoring at 8.5, presented the lowest relative values. This slight reduction suggests opportunities to improve the clarity of system states and the predictability of the relationship between the performed gesture and the resulting system behavior. Such aspects are aligned with established principles in the interaction literature concerning users' mental models. Nonetheless, even these items indicate positive evaluations and do not compromise the overall consistency of the strong usability perception demonstrated across the responses.

5.3 Discussion

The usability evaluation conducted using the SUS resulted in an average score of 92.5, which places the system within the "Best Imaginable" usability category according to the adjective rating scale proposed by Bangor et al. [47]. This classification indicates that participants perceived the continuous gesture input method as extremely easy to learn and use. This outcome is consistent with the pattern observed in the item-by-item analysis, in which all normalized items received high scores, suggesting a clear, stable, and low-complexity user experience. Table 4 presents the correspondence between these adjectives and the mean SUS values reported in previous studies, supporting the interpretation of participants' evaluations.

Table 4. Descriptive statistics of SUS scores for adjective ratings (Adapted from [47])

Adjective	Mean SUS Score
Worst Imaginable	12.5
Awful	20.3
Poor	35.7
OK	50.9
Good	71.4
Excellent	85.5
Best Imaginable	90.9

Considering the 95% confidence interval (89.5–95.5), the lower bound remains within the range associated with the highest levels of Bangor et al.'s adjective rating scale [47]. Although 89.5 is slightly below the typical mean assigned to the "Best Imaginable" category (90.9), it still lies in the upper region of the scale and above the mean value for the "Excellent" category (85.5), as presented in Table 3. This indicates that, even under a conservative estimate, perceived usability remains at a high level consistent with systems regarded as exceptionally easy to learn and use. Thus, the "Best Imaginable" classification attributed to the mean is statistically supported, as the entire interval remains above the values commonly associated with highly usable systems, even while reflecting the variability inherent to studies with small samples.

The interpretation of this score can be further contextualized using established references in the literature. Sauro and Lewis [40] report that the global SUS mean for systems evaluated in prior studies is approximately 68, a value typically associated with acceptable usability. Lewis and Sauro [48] add that systems scoring above 80 tend to be perceived as highly usable and well designed. Therefore, the score obtained in this study places the proposed method far above acceptability thresholds and within the range associated with positive user experiences. This interpretation is further supported by qualitative feedback collected during the experiment, in which users described the method as easy to learn, clear in its functioning, and not requiring technical support.

The quantitative performance metrics indicate that participants were able to complete the text entry tasks with controlled error rates and a low gestural interaction cost. Although interaction errors occurred during input, they were consistently corrected before task completion, resulting in accurate final transcriptions while maintaining a low average number of gestures per character. This pattern suggests that the predictive mechanism supported error recovery without increasing interaction effort. In parallel, the usability assessment reinforces this interpretation, as the analysis of SUS items Q3 and Q6 points to opportunities for improving visual feedback and system state predictability, both aspects that are directly related to users' ability to anticipate system behavior.

Overall, the results reinforce the perceived feasibility of the method from a usability standpoint for smartwatch text entry. The combination of perceived usability, rapid learning, and the absence of evident interaction barriers suggests that continuous gesture recognition is a promising approach for contexts where interaction space is limited. These findings provide a consistent foundation for future refinements and for conducting additional studies that incorporate comparative analyses with other input methods, specific user populations, and long-term usage evaluations.

5.4 Educational and accessibility applications

The high usability scores observed in this study, particularly the combination of ease of use, low perceived complexity, rapid learning, and confidence during interaction, provide empirical indications of how the proposed method may be applicable to educational and accessibility contexts. Although the experiment did not involve children or users with motor impairments, the normalized SUS results reveal interaction characteristics that are relevant to such settings.

Elevated scores for items related to rapid learning (Q7), confidence during use (Q9), and perceived functional integration (Q5) indicate that participants understood and operated the system without requiring additional guidance. In educational environments, especially those involving mobile devices, interfaces with low cognitive demand tend to support sustained engagement, as discussed by Almusawi et al. [2]. The findings of this study indicate that the method exhibits precisely this profile, allowing interaction to occur without competing with the attention required for pedagogical tasks.

From an accessibility standpoint, the results highlight relevant interaction characteristics. Item Q2, which evaluates perceptions of excessive complexity, received one of the highest normalized scores, indicating that users did not perceive the system as complex. Item Q8, related to perceived difficulty of use, also received a high score, suggesting that performing the gestures was not experienced as effortful. This pattern aligns with interaction models based on simple forms, such as lines and curves, which require less fine motor precision. Xuanfeng [6] notes that low-effort gestural modalities can support the participation of learners with motor limitations, a perspective consistent with the results obtained in this study.

The use of simple gestures is also related to research on cognitive development and early learning. Mustar et al. [49] demonstrate that interfaces based on geometric shapes facilitate spatial understanding and reduce cognitive load in learning tasks. Complementarily, Chen [50] discusses how adaptive mechanisms can support gesture perception and interpretation in wearable systems, reinforcing the suitability of simplified input models for educational environments. Although the present study did not involve children, the pattern of rapid familiarization and low cognitive demand observed suggests potential for future investigation in such contexts.

Furthermore, studies on multimodal interaction and gesture use in compact devices indicate that such approaches can be integrated into digital learning environments. Tian and Wang [51] show that multimodal techniques enhance interaction on small devices, and Lu et al. [52] demonstrate that gesture-recognition mechanisms can operate with high accuracy and low computational demand. These results suggest that simple, easily recognizable gestures are well suited to mobile and wearable systems in pedagogical and assistive contexts. Rahimian et al. [53] similarly highlight the value of multimodal models for supporting engagement in educational systems.

Overall, the SUS results provide an empirical basis for considering the proposed method in future studies focused on education and accessibility. Although they do not imply direct effectiveness in these contexts, the findings indicate that the interaction afforded by the method is compatible with the cognitive, motor, and contextual constraints commonly associated with such environments. Future investigations should therefore involve children, educators, and users with motor limitations, enabling a comprehensive evaluation of the method's suitability, usefulness, and impact on educational and inclusive practices.

5.5 Challenges and opportunities

The development of the method also revealed several challenges that can guide future improvements. Adapting the approach to different languages and expanding the word dictionary are examples of enhancements that could broaden the system's applicability. These perspectives indicate directions for making the method more versatile and accessible, fostering personalized and inclusive interactions on wearable devices.

Additionally, the performance of the method is directly related to the quality and extent of the word dictionary used. A comprehensive and accurate dictionary is essential for providing relevant and coherent suggestions during the text input process.

Future research should explore multilingual extensions of the predictive dictionary, particularly for languages that share the Latin alphabet, such as Portuguese, Spanish, and French. In these cases, adaptation requires only updates to the dictionary content, without structural changes to the gesture recognition model. This characteristic facilitates scalability and supports the potential expansion of the method to broader user groups. Comparative evaluations with users from different linguistic and cultural backgrounds are also recommended to strengthen the method's generalizability and global applicability.

6 FINAL CONSIDERATIONS

This work presented and evaluated a gesture-based text input method for smartwatches using continuous gesture recognition, Naïve Bayes classification, and a trie-based predictive dictionary. The proposed approach was designed to mitigate the limitations of text entry on small-screen devices by offering an alternative interaction mechanism that does not rely on small touch targets and reduces the need for precise finger input. The results showed that users were able to complete the text entry tasks and perceived the method as supporting an accessible and consistent user experience. In addition to the subjective usability results, the quantitative performance analysis indicated that participants completed the tasks with controlled error rates and a low gestural interaction cost, suggesting that the method does not impose excessive motor or cognitive demands during use.

The empirical evaluation, conducted with volunteer participants through the SUS questionnaire, revealed a highly positive perception of usability. Participants found the method easy to learn, intuitive, and functionally coherent, even without prior training or technical support. The use of continuous gesture recognition was perceived as contributing to a clear and straightforward interaction, and although some refinements, such as prototype standardization and improved visual feedback, remain possible, the overall results confirm the feasibility of the proposed approach from a usability perspective.

While the current implementation and evaluation were limited to a specific experimental setting and language, the modular architecture of the system allows for straightforward adaptation through the replacement or expansion of the word dictionary. This characteristic supports future extensions to other languages that share similar writing systems and provides flexibility for further experimentation.

Future work will focus on refining the predictive dictionary, expanding the set of test phrases, and conducting controlled studies with larger participant groups. Additional investigations should include longitudinal evaluations, comparative studies with existing text-entry methods, and experiments involving specific user populations and application contexts. These efforts will contribute to a deeper empirical understanding of the method and support its continued development and validation.

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