How They Type: Eye and Finger Movement Strategies in Typing of Individuals with Cerebral Palsy

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Abstract

Typing is essential for communication, yet the input behavior of individuals with cerebral palsy (CP) remains underexplored. We investigated 31 CP typists and 31 non-disabled controls using keystroke logging, eye tracking, and motion capture. Our study found that CP typists were slower and less rhythmically stable, but by prioritizing accuracy, their overall keyboard efficiency was comparable to controls. They adopted compensatory visual strategies such as shorter and more frequent fixations, greater reliance on the keyboard, and more gaze shifts, and displayed diverse finger usage strategies from single-finger to multi-finger input. We found that using more fingers did not necessarily result in faster typing. Subtype analysis showed spastic CP typists followed a "slow but steady" rhythm with consistent inter-key intervals, whereas athetoid CP typists exhibited a "fast but unstable" rhythm with greater variability, highlighting distinct mechanisms of typing in CP and providing insights for personalized assistive technologies.

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CCS Concepts

• **Human-centered computing** → **Accessibility**; *Empirical studies in accessibility*; • **Applied computing** → Health informatics.

Keywords

Individuals with Cerebral Palsy, Fine Motor Impairments, Typing Strategies, Finger-to-Key Mapping Patterns, Eye-tracking analysis

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1 Introduction

In today's digital society, keyboard typing has become a core foundation for communication, productivity, and information accessibility. Efficient typing not only enhances participation in digital and social environments but is also an indispensable skill for modern work, study, and everyday life. Studies have shown that typing efficiency depends on consistent finger–key mapping, preparation for the next keystroke, and minimization of hand movement [7], indicating that finger dexterity and fine-motor control are crucial for typing.

However, existing research remains limited in its understanding of the behavioral mechanisms of individuals with fine motor impairments in real-world text entry contexts. Cerebral palsy (CP) is a group of neurological disorders caused by early developmental brain damage and is primarily characterized by impairments in movement and posture [12, 20, 31]. Typical manifestations include reduced manual dexterity and restricted movement. According to estimates by the World Health Organization, the prevalence of CP is approximately 1–4 per 1,000 live births, which implies that tens of millions of people worldwide live with CP [17]. These individuals live under long-term motor uncertainty and frequently need to perform keyboard input, yet often can only rely on one hand or a very limited number of fingers.

With rapid technological development and the growing emphasis on inclusivity, "technology for good" has become a key driver for empowering people with disabilities and marginalized groups, enabling more independent access to the digital world [1, 22]. In the field of Human–Computer Interaction (HCI), researchers have developed various assistive technologies to enhance text input for individuals with motor impairments, such as scanning keyboards (e.g., SAK), head-controlled interfaces, and eye-tracking-based systems [16, 29]. Despite their potential, prior research has primarily focused on macro-level performance metrics, such as input speed and accuracy, while offering limited insight into how individuals actively regulate their behavior under long-term motor constraints to maintain controllability and fluency in text entry. Simply stating that users "type more slowly" or "make more errors" does not explain how they redistribute attentional resources, adjust movement rhythms, or simplify finger strategies to achieve stable expression. Revealing these adaptive regulation mechanisms is essential for moving from descriptive observations to theory-driven design principles, which constitutes the core motivation of this study.

Previous studies have identified two main pathways for improving the accessibility of text entry. On the one hand, automatic error correction and predictive mechanisms can significantly reduce the burden of motor-related errors and thereby enhance overall usability [11]. On the other hand, adaptive keyboard layouts dynamically generated based on individual motor characteristics have been shown to effectively improve both input efficiency and accessibility [18, 32]. Therefore, systematically characterizing the visual–motor coordination patterns and temporal rhythmic features of CP users in real-world input scenarios can not only provide empirical foundations for these technologies, but also contribute to understanding how individuals maintain functional performance under constrained motor conditions by regulating attention and movement strategies.

Specifically, we recruited 31 participants with CP, covering a range of motor impairment levels [5], finger function abilities [19], age groups, and educational backgrounds. For comparison, we also collected data from 31 non-disabled typists. This study focuses on hand movement characteristics and eye-tracking data related to typing performance. By systematically comparing behavioral differences between CP typists and non-disabled typists, we aim to reveal how individuals under long-term motor constraints construct stable and sustainable input strategies, and to provide theoretical foundations for the development of personalized typing assistance systems for people with CP.

The key contributions of this research can be summarized as follows:

(1) Our results show that CP typists type more slowly and exhibit less stable typing rhythms than non-disabled typists. However, by prioritizing accuracy and minimizing unnecessary corrections, they maintain a level of keyboard efficiency comparable to that of non-disabled users (defined as the proportion of effective keystrokes relative to total keystrokes). This reflects an active self-regulation strategy oriented toward controllability, in which CP typists deliberately trade speed for precision.
(2) The analysis reveals distinctive gaze patterns among CP typists, characterized by shorter and more frequent fixations, greater reliance on the keyboard, and more frequent gaze shifts between the screen and the keyboard, indicating that they operate under a sustained high-monitoring input mode.
(3) CP typists exhibit diverse finger usage patterns, ranging from single-finger typing to multi-finger coordination strategies, reflecting varied adaptations to their motor limitations. We also found that using more fingers did not necessarily result in faster typing.
(4) Subtype analysis shows clear differences in typing rhythm: spastic CP typists demonstrate a "slow but steady" pattern with more consistent inter-key intervals, whereas athetoid CP typists display a "fast but unstable" pattern characterized by greater variability in inter-key intervals, highlighting the influence of neurological differences on input regulation strategies.

To support further research on this important topic, we will make our dataset on typing in CP typists publicly available. This will allow other researchers to build on our work and contribute to improving the accessibility and efficiency of typing solutions for people with CP.

2 Related Work

2.1 Motor and Visual Perceptual Impairments in CP

CP is a group of motor disorders caused by abnormalities in brain development, and it is often accompanied by impairments in cognition, sensation, and vision. Different subtypes of CP are characterized by distinct motor manifestations, including spastic, ataxic, and dyskinetic forms. Individuals with spastic CP typically experience persistent muscle contractions that restrict the range of limb motion. In contrast, those with ataxic CP often demonstrate unstable motor control and tremors [24]. Each type of motor impairment may influence typing strategies in different ways, which is precisely the focus of our investigation.

In addition to motor challenges, individuals with CP often experience visual impairments. A population-based study in Croatia involving 419 children with CP reported that 66.5% had some degree of visual impairment, and 11% had severe impairment [27]. These deficits commonly manifest as difficulties in sustaining and shifting attention, impairments in spatial localization, reduced visual processing speed, and limitations in object and face recognition [6]. Prior research on the relationship between visual and motor impairments in CP has mainly focused on motor function assessment, visual perceptual deficits, and their interactions. For example, studies by Striber et al. [27] and Ghasia et al. [8] found that greater motor limitations were associated with more pronounced visual impairments in children with CP. However, although these findings highlight the close link between motor and visual impairments, most prior work has emphasized everyday motor functions or general hand–eye coordination, with limited attention to specific cognitive–motor integration tasks such as typing.

2.2 Input Behaviors of Users with Motor Impairments in HCI

In human–computer interaction research, keyboard adaptation is an important approach to improving input efficiency for users with motor impairments. Mitchell et al. [18] proposed the concept of ability-based keyboards, which generate customized layouts tailored to an individual's motor abilities by analyzing their movement patterns. Wang et al. [30] developed algorithmic modeling and predictive mechanisms to compensate for operational deviations caused by tremor and bradykinesia in individuals with Parkinson's disease. Beyond traditional keyboards, various alternative input methods have been designed to accommodate the motor characteristics of individuals with CP. For example, scanning keyboards allow users to select characters sequentially using a single switch, although input speed remains limited [23]. Another alternative is head-controlled interfaces, in which head orientation drives cursor movement or virtual keyboard operation. Velasco et al. [28] demonstrated that cursor trajectories under head control in individuals with CP can be modeled using Fitts's law, but are significantly less stable than those of typically developing users. In addition, motion-based and sensor-based input methods have increasingly been applied in rehabilitation and input training for children with CP, showing potential to improve motor control and task performance [25].

Eye-tracking technology provides individuals with CP an effective non-contact input method. Jeevithashree et al. [9] proposed a gaze-controlled interface that enables individuals with severe speech and motor impairments to perform simple computer operations through eye movements. Kumar et al. [13] further developed a touch–gaze hybrid input method that combines eye tracking with touch interaction, significantly improving input accuracy and efficiency. Zhao et al. [33] explored gaze speedup techniques in virtual reality, integrating eye tracking with motion-based interaction to achieve more precise gesture input in immersive environments. These technological advances not only improve input efficiency in experimental settings but also demonstrate the potential to enhance communication and social participation in practical applications. Children and adolescents with CP, despite facing motor and cognitive challenges when using computers and augmentative and alternative communication devices, can significantly improve their communication abilities and social participation through such technologies [23].

2.3 Assessment Framework for Typing Behavior Analysis

In general human–computer interaction and text entry research, a series of typical performance metrics are commonly collected, such as words per minute (WPM), inter-key interval (IKI), error rate, and keyboard efficiency, to comprehensively evaluate input speed, accuracy, and efficiency [4, 7, 10, 26]. These measures have become the standard baseline for cross-technology comparisons. However, for individuals with cerebral palsy, who often present with significant impairments in both motor and visual functions, relying solely on these macroscopic performance metrics is insufficient to reveal the underlying mechanisms of their input behavior. Therefore, in our experiment we not only collected the conventional metrics, but also incorporated CP-specific dimensions: on the motor side, we examined the number of fingers used, the distribution and clustering of finger usage, and the dominant finger employed; on the visual side, we analyzed the number of fixations per minute, the average duration of each fixation, the proportion of gaze time distributed between the keyboard and the screen, and the proportion of invalid fixation time. By including these extended metrics, we aim to gain deeper insights into the finger-use strategies and visual attention allocation strategies adopted by individuals with cerebral palsy during typing, thereby contributing to a better understanding of their input habits and informing the design of assistive technologies.

3 Method

3.1 Experimental Design

We designed a typing task to collect typing log data. Each time a text stimulus was displayed on the screen, participants were asked to type the content according to their usual typing habits. During the typing process, participants could correct errors before submitting each text stimulus. In addition to the typing data, we recorded their finger movements and keystrokes on the keyboard using a camera mounted above the keyboard as shown in Fig. 1, and captured their eye gaze using Tobii Pro Glasses.

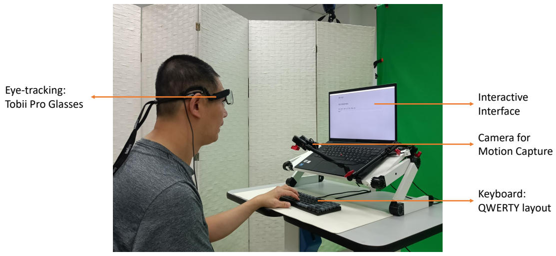
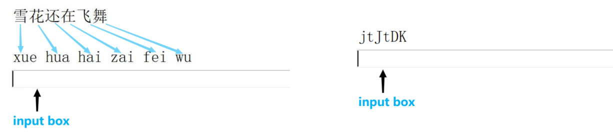


Figure 1: A participant with CP completed the typing task using the experimental equipment. The setup included motion capture, keyboard logging, and eye tracking.



(a) A Chinese sentence with pinyin

(b) A random string

Figure 2: The typing materials are shown in two conditions. The Chinese sentence condition (left) presents Chinese sentences represented in pinyin, with spaces separating the pinyin notation for each character. The random string condition (right) consists of a random sequence of uppercase and lowercase letters.

3.2 Participants

62 participants (31 CP typists: Mean age = 23.64 years, Standard Deviation = 7.67 years; 31 non-disabled typists: Mean age = 24.38 years, Standard Deviation = 3.99 years) participated in the experiment. Among the 31 CP typists, 20 were classified as spastic type and 11 as athetoid type.

All participants gave informed consent prior to participation and were paid after they completed the experiment. The study adhered to the principles of the Declaration of Helsinki and was approved by the Institutional Review Board of our institute.

3.3 Materials

To comprehensively examine the typing performance of individuals with CP, this study designed two types of text input tasks. The first task consisted of simple and comprehensible Chinese sentences, which were converted into *pinyin* (a system that uses the Latin alphabet to represent Chinese pronunciation, showing how to pronounce Chinese characters). Considering that some participants with CP have limited educational backgrounds, pinyin input better reflects their actual usage scenarios and provides a realistic measure of daily communication performance. The second task involved typing random strings, with the aim of eliminating the influence of language proficiency and semantic memory, thereby capturing purer data on keystroke dynamics and visual search behavior. By comparing the results of these two tasks, we were able to disentangle the respective contributions of language processing and motor/visual control factors to typing performance. Specifically, the pinyin task included 30 sentences, as shown in Fig. 2a, while the random string task included 10 sentences, as shown in Fig. 2b. In the following text, we refer to these two materials as "*pinyin*" and "*random*".

3.4 Apparatus

This experimental setup consisted of three parts: motion capture, keyboard logging, and eye tracking, as shown in the Fig. 1. The keyboard logging and motion capture were synchronized to begin simultaneously, allowing for alignment of corresponding frames during data analysis.

Motion Capture: A camera was placed directly above the keyboard to record hand movements and keystrokes. The Python libraries `MediaPipe` and `OpenCV` were used to track the movements of each joint of both hands in real time at a frame rate of 20 frames per second (fps), where each frame corresponds to 0.05 seconds and 10 frames represent a 0.5-second interval. `MediaPipe` is a comprehensive library for various computer vision tasks, including hand tracking and hand feature point detection. It provides three-dimensional coordinates for hand feature points. This vision-based methodology proves particularly advantageous for studying participants with motor impairments, as it eliminates the need for physical sensor attachments that could interfere with natural typing postures—a common limitation of traditional motion capture systems. Furthermore, the system's minimal hardware dependency (requiring only a single calibrated camera) ensured both experimental flexibility across environments and reduced setup complexity compared to conventional multi-sensor laboratory configurations.

Keyboard Logging: Typing software, implemented in Python, provided an interactive interface that allows participants to input the required letters based on on-screen prompts. The software recorded each keystroke, including modifier keys like Shift and Ctrl, along with its corresponding frame and timestamp. At the end of each session, participants received feedback on their typing efficiency. A physical keyboard with a standard QWERTY layout was used for the typing tasks.

Eye Tracking: Tobii Pro Glasses eye-tracking glasses were used to capture gaze shifts between the keyboard and the screen. Calibration was performed after putting on the glasses to ensure accurate gaze points.

3.5 Procedure

Before the experiment began, participants were informed that the study aimed to examine the typing habits of CP typists, with the goal of identifying ways to improve their typing efficiency. Before starting the typing task, participants wore the eye-tracking glasses to monitor their gaze shifts and points of attention. Once the eye tracker was properly worn, it was calibrated to ensure accurate gaze points.

Next, the typing task was introduced to the participants. After completing each text stimulus, they were instructed to press the ENTER key to submit and move on to the next text stimulus. After typing twenty text stimuli, participants took a break, during which we could also check if the equipment was functioning properly. At the end of the experiment, participants were required to fill out a questionnaire that asked about their demographic information, the cause of their disability, the usability of their fingers, typing experience, and other related factors (all factors detailed in Section 6.4). After completing the experiment, each participant was rewarded with 50 RMB.

4 Data analysis

We first compared the typing performance, eye gaze patterns, and finger usage between non-disabled typists and CP typists. Then, we analyzed the typing habits of CP typists and used clustering to categorize them into five distinct groups, examining their finger usage patterns for each key mapping. Finally, we examined the correlation between typing efficiency and various factors including disability level, the distribution and frequency of eye movements between the screen and keyboard, identifying key factors that influenced typing efficiency in CP typists.

4.1 Preprocessing

(1) Transformation to Keyboard Coordinate System: To enable comparison between participants, we applied a perspective transformation to each video frame, aligning the tracked hand positions with a predefined keyboard coordinate system where the top-left corner of the 'Escape' key is set as the origin (0, 0). Assuming the original camera coordinates are (x, y) and the predefined keyboard coordinates are (x', y'), the perspective transformation can be expressed as:

$$\begin{pmatrix} x' \\ y' \\ w \end{pmatrix} = \mathbf{H} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix},$$

where $\mathbf{H}$ is the perspective transformation matrix. The transformed coordinates (x', y') can be further processed normalizing with the third coordinate w as follows:

$$x'' = \frac{x'}{w}, \quad y'' = \frac{y'}{w},$$

where (x'', y'') are the normalized coordinates.

(2) Key Press Identification: For each key press event recorded in the experiment, finger identification was performed by analyzing hand position data within a temporal window of 10 frames (20 fps) centered around the key press. The most frequently observed finger within this 500-millisecond window was algorithmically determined as the active key presser.

(3) Outlier Removal: Occasionally, disruptions or pauses in the typing experiment occurred due to equipment issues. To ensure data integrity, we employed the Isolation Forest algorithm to detect and remove abnormal samples and text stimuli, refining the dataset for further analysis. First, define the dataset as $D = \{x_1, x_2, \ldots, x_n\}$, where x_i represents the i-th sample in the dataset. Then define the scoring function $s(x_i)$ as:

$$s(x_i) = 2^{-\frac{E(h(x_i))}{c(n)}},$$

where $E(h(x_i))$ is the average path length of the sample x_i in the isolated tree and $c(n)$ is a constant used to normalize the path lengths. Based on the score $s(x_i)$ and the threshold τ, whether a sample is an anomaly is determined. Finally, by removing anomalous points from the dataset, a refined dataset is obtained:

$$D' = \{x_i \in D \mid s(x_i) \le \tau\}.$$

4.2 Metrics

4.2.1 *Typing Performance.*

To evaluate typing efficiency in both random string condition and sentence condition, we used several metrics:

(1) **Words per Minute (WPM)**: This is calculated directly from the raw typing logs. We define the total number of typed characters, including spaces, for each text stimulus as N, and the total typing duration as T. WPM is then calculated as:

$$\text{WPM} = \frac{N}{T}.$$

(2) **Inter-Key Interval (IKI)**: This measures the average time interval, in milliseconds, between consecutive keystrokes, inclusively counting modifier keys and error corrections. For each text stimulus, assuming the time interval between each two consecutive character keystrokes is d_i and the number of keystrokes is n, IKI is defined as:

$$\text{IKI} = \frac{1}{n-1} \sum_{i=1}^{n-1} d_i.$$

(3) **Inter-Key Interval Variability (IKIv)**: This measures the stability of typing rhythm by evaluating the variation of inter-key intervals across a text stimulus. For each text stimulus, assuming the time interval between two consecutive keystrokes is d_i and the number of keystrokes is n, the standard deviation of inter-key intervals is defined as:

$$\text{IKIv} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n-1} (d_i - \overline{d})^2},$$

where $\overline{d}$ denotes the mean IKI. A higher IKIv indicates greater inconsistency in keystroke timing, reflecting reduced typing rhythm stability.

(4) **Uncorrected Error Rate (UER, %)**: The UER quantifies typing accuracy by comparing the typed sequence s with the target sequence *label*, and is defined as:

$$\text{UER} = \frac{d_{DL}(s, label)}{\max(|s|, |label|)},$$

where d_{DL} denotes the Damerau–Levenshtein edit distance and $|s|$ the sequence length.

(5) **Keyboard Efficiency (KE)**: The KE represents the ratio of characters in the final input to the total number of keystrokes:

$$\text{KE} = \frac{|s|}{K},$$

where $|s|$ is the length of the final input sequence and K is the total number of keystrokes.

4.2.2 Eye Gaze. To investigate the gaze shifts and visual attention during the typing process of CP typists, we measured the following metrics:

(1) **Average fixations per minute**: This metric refers to the number of times an individual's gaze fixates on a specific point or area within one minute.
(2) **Average fixation duration (ms)**: This metric refers to the average amount of time, that a person's gaze remains fixed on a single point or object during tasks like reading or typing.
(3) **Gaze shifts**: This metric is defined as the number of gaze transitions between the screen and the keyboard during the input of a text stimulus.
(4) **Proportion of Keyboard viewing**: This metric refers to the proportion of time spent looking at the keyboard during the entire typing process relative to the total time.
(5) **Proportion of ineffective time**: This metric refers to the proportion of time spent neither looking at the keyboard nor at the screen during the entire typing process relative to the total time.

4.2.3 Motion Analysis. For this analysis, we include both letters and functional keys such as the spacebar and Caps Lock.

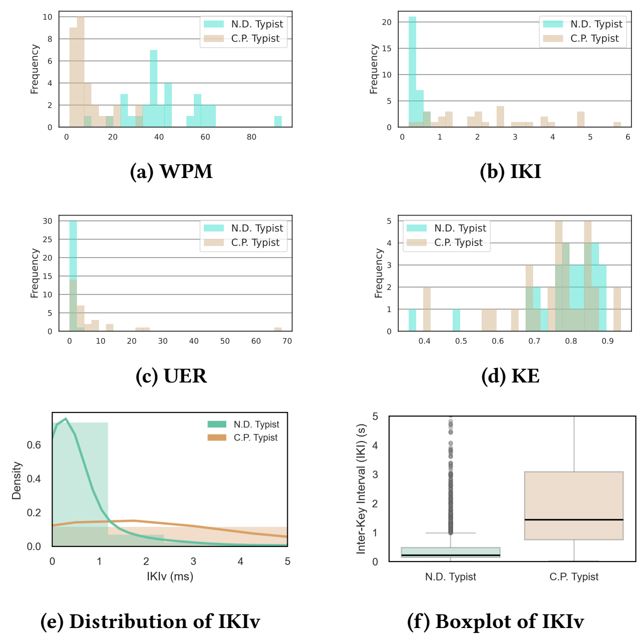
(1) **Number of fingers used**: This quantifies the total number of distinct fingers engaged in typing. During the processing of typing videos, minor image recognition errors may occur, leading to the identification of fingers that were not actually used. To address this issue, we excluded fingers that were recorded as being used fewer than 20 times.
(2) **Mainly Used Finger**: This metric refers to the finger that contributes the highest number of keystrokes during the typing task. For each participant, we counted the total keystrokes performed by each finger and identified the finger with the maximum count as the dominant finger.
(3) **Finger Clusters**: This metric refers to the classification of participants' finger usage patterns into different categories. Based on the distribution and combination of fingers engaged during typing, we applied clustering analysis to group participants into five distinct finger usage strategies.

5 Comparison Between non-disabled typists and CP typists

We collected a total of 77,643 keystrokes across the two groups, with 40,941 keystrokes collected from CP typists. Table 1 compared the statistical test results between CP typists and non-disabled typists across several dependent variables.

5.1 Typing Performance

Results. The analysis demonstrates that CP typists consistently underperform compared to their non-disabled counterparts across three primary typing performance metrics—WPM, IKI, and UER—as shown in Fig. 3a, 3b, and 3c. In particular, even the fastest WPM observed among CP typists only corresponds to the lower–middle range of WPM typically achieved by non-disabled typists. The IKI of CP typists is substantially longer and exhibits significantly higher variability, reflecting less efficient and more inconsistent typing rhythms. Moreover, the UER of CP typists is considerably elevated and displays a polarized distribution pattern.



(a) WPM
(b) IKI
(c) UER
(d) KE
(e) Distribution of IKIv
(f) Boxplot of IKIv

Figure 3: Typing performance metrics comparing N.D. typists (non-disabled typists) and C.P. typists (cerebral palsy typists).

In addition, as shown in Fig.3e and Fig.3f, CP typists show markedly greater variability in IKIv, further indicating unstable temporal control during typing. By contrast, no significant difference was observed between groups in keyboard efficiency (KE), as shown in Fig. 3d.

We compared the differences between non-disabled typists and CP typists for both the pinyin condition and the random condition. The observed patterns of metric differences remained consistent across both conditions. Therefore, in subsequent analyses, we do not differentiate between the two conditions.

Discussion. The observed discrepancies in typing performance between CP typists and non-disabled typists suggest that physical limitations inherent in CP may significantly hinder typing speed and accuracy, likely due to variations in the severity and type of motor impairments, which affect participants differently and result in more dispersed data. The higher UER, coupled with its polarizing distribution, suggests that while some CP typists may develop compensatory strategies to mitigate errors, others struggle more profoundly. At the same time, we observed that the keystroke rhythm variability (IKIv) of CP typists was significantly higher than that of non-disabled typists, indicating that their typing process is not only slower overall but also less stable in terms of rhythm control. The differences in IKIv reveal additional challenges faced by CP typists in temporal control and motor coordination, suggesting that their input behavior is constrained by more complex motor control limitations.

Interestingly, despite the differences in WPM, IKI, and UER, KE shows no significant difference between the two groups. This can

	Measure	CP typists		Non-disabled typists		M.-W.Stat.		
		M	SD	M	SD		U	P
Background	Age	23.64	7.67	24.38	3.99	○	229.5	0.073
	Typing experience	3.11	2.65	5.81	2.87	●	188.6	0.001
Performance	WPM -pinyin	8.77	4.09	39.66	14.99	●	11	<0.001
	-Random	4.25	2.53	8.02	5.36	●	65.3	0.001
	IKI (ms) -pinyin	2.33	0.81	0.39	0.13	●	956	<0.001
	-Random	2.89	1.64	0.68	0.38	●	421.3	<0.001
	IKIv (ms) -pinyin	708	1057	140	197	●	543.9	<0.001
	-Random	2303	1278	237	124	●	893.2	<0.001
	UER -pinyin	9.37	16.61	0.42	1.08	●	855	<0.001
	-Random	11.23	18.39	0.78	2.31	●	211.3	<0.001
	KE -pinyin	0.75	0.19	0.76	0.11	○	458.9	0.318
	-Random	0.48	0.21	0.51	0.14	○	413.9	0.145
Eye gaze	Average fixations per minute	125.60	55.84	78.38	44.48	●	726	<0.001
	Average fixation duration (ms)	488.09	98.69	1089.24	889.62	●	268	<0.001
	Gaze shift	4.29	2.12	2.02	0.82	●	317	<0.001
	Proportion of Keyboard	0.32	0.27	0.05	0.12	●	997	<0.001
	Proportion of ineffective time	0.16	0.35	0.14	0.27	○	831.5	0.0916
Motion Analysis	Number of fingers used	4.67	2.66	6.88	2.06	●	233	0.001

Table 1: Comparison of the statistical test results between CP typists and non-disabled typists across several dependent variables. M = mean, SD = standard deviation. Mann–Whitney U tests were used. ●indicates significant differences, ○non-significant.

be partly explained by the different strategies employed by non-disabled typists, who may prioritize speed over accuracy during their initial typing. Because the cost of correcting errors is relatively low for them, they often sacrifice initial accuracy for speed, knowing they can quickly make corrections afterward. In contrast, CP typists face higher physical and cognitive costs when correcting errors due to their motor limitations. As a result, they might be more cautious with their initial typing to avoid the need for subsequent corrections, leading to a similar level of keyboard effectiveness despite slower speeds and higher error rates.

This suggests that while non-disabled typists can afford to trade off some initial accuracy for greater speed, CP typists may need to focus more on accuracy from the outset to maintain overall effectiveness, even if it results in slower typing. These insights emphasize the importance of designing assistive technologies that can reduce the physical and cognitive burden of error correction for CP typists, potentially allowing them to adopt strategies that improve both their speed and accuracy. For example, AI-powered tools like automatic correction based on large language models or predictive text completion can help reduce typing errors and speed up input. Such technologies can alleviate the pressure on CP typists during text entry, improving their overall typing efficiency.

5.2 Eye Gaze

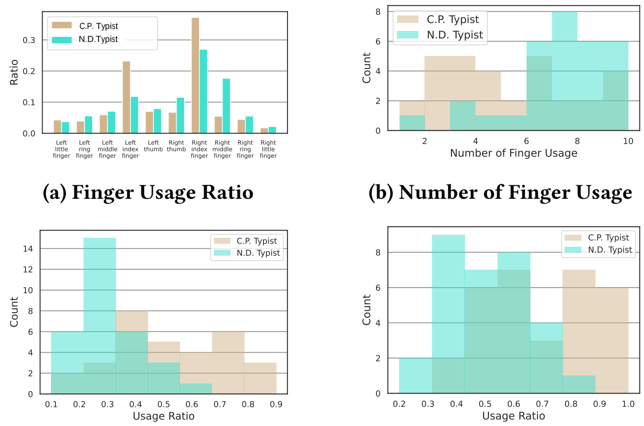
Results. As shown in Table 1, eye-tracking analysis revealed a significant difference in the average number of fixation points per minute between CP typists and non-disabled typists. In particular, CP typists had an average of 125.60 fixation points per minute, whereas non-disabled typists averaged 78.38 fixation points per minute. The duration of each fixation point was significantly shorter for CP typists. The average duration per fixation for CP typists was 488.09 ms, compared to 1089.24 ms for non-disabled typists. CP typists spent 32% of their time looking at the keyboard, whereas those without disabilities spent only 5%. Moreover, gaze shift analysis revealed that CP typists exhibited an average of 4.29 gaze shifts per sentence, while non-disabled typists exhibited 2.02 gaze shifts per sentence. On the contrary, the experiment did not find any significant difference in proportion of ineffective time between the two groups.

Discussion. Eye-tracking analysis revealed clear differences in visual strategies between CP typists and non-disabled typists. CP typists showed more fixation points per minute but with shorter durations, indicating difficulty in maintaining stable gaze and a need for frequent visual adjustments, likely due to limitations in ocular motor control or sustained attention [2]. They also spent 32% of their time looking at the keyboard, compared to only 5% for non-disabled typists, suggesting a reliance on frequent key-position confirmation to compensate for motor control deficits. While this strategy may help reduce errors, it also diverts attention from the screen, reducing fluency. In addition, CP typists exhibited more gaze shifts per sentence (4.29 vs. 2.02), reflecting greater visuomotor coordination demands and a compensatory "high confirmation" strategy. However, no significant group difference was observed in ineffective gaze time, suggesting that despite more fragmented patterns, CP typists still use their visual resources efficiently.

Overall, CP typists adopt distinctive visual strategies—shorter and more frequent fixations, greater keyboard reliance, and more gaze shifts—which highlight the need for assistive technologies that reduce visual confirmation and gaze-switching demands, such as salient key prompts, highlighted keys, or predictive input features.

5.3 Finger usage patterns

Results. The comparison between typists with CP and non-disabled typists reveals significant differences in finger usage during typing, as shown in Fig. 4a. CP typists predominantly rely on the index fingers of both hands, whereas non-disabled typists most frequently use the right index and middle fingers. Interestingly,



(a) **Finger Usage Ratio**

(b) **Number of Finger Usage**

(c) **Usage Ratio of the Most Frequently Used Finger**

(d) **Usage Ratio of Top Two Fingers**

Figure 4: Comparison of finger usage patterns between N.D. typists (non-disabled typists) and C.P. typists (cerebral palsy typists).

CP typists use their middle fingers far more frequently than non-disabled participants.

Further analysis of the number of fingers used shows that CP typists use significantly fewer fingers overall compared to non-disabled typists, as illustrated in Fig. 4b. This limited finger usage among CP typists is evident from the fact that nearly half could perform over 50% of their typing tasks using just one finger, as depicted in Fig. 4c. This stands in stark contrast to non-disabled participants, among whom only one individual managed the same feat, with the majority using their most frequently used finger for less than 30% of the tasks.

Additionally, the usage frequency of the two most commonly used fingers was analyzed to demonstrate the reliance on only a few fingers for typing, as presented in Fig. 4d. The findings suggested that most people with disabilities completed 50% of their typing tasks with just two fingers.

Discussion. The analysis showed that the index finger is predominantly preferred by CP typists, with a strong reliance on the index fingers of both hands. This differs from the general population, where finger usage is more evenly distributed among all fingers.

In terms of motor neural control, there are significant differences between the functions of the index and middle fingers. For non-disabled typists, the middle finger typically exhibits better independent control and flexibility, allowing it to be frequently used in typing. The middle finger's ability to contribute to keystrokes helps distribute the workload across the fingers more evenly. This is partly due to its neural connections, which enable efficient stimulation of the muscles required for precise and independent movement.

However, CP typists often face limitations in motor function, particularly in the fine motor control of the middle finger. Due to impaired neuromuscular coordination, the middle finger is less flexible and harder to control in a way that matches the dexterity of non-disabled typists [14, 15]. As a result, CP typists tend to rely more heavily on the index fingers of both hands, as the index finger has a simpler neural pathway and requires less complex motor control to perform keystrokes. This leads to a significantly reduced frequency of middle finger use in CP typists. Such differences in finger usage reflect the strategic adaptations made by CP typists to accommodate their physical limitations and optimize their typing efficiency within their capabilities.

Moreover, the presence of a clear threshold at 0.7 (the blue section in Fig. 4d) distinguishes typing habits and indicates identifiable patterns in finger usage. In the next section, we will discuss the clustering-based classification of CP typists with different typing habits, as well as the factors affecting their typing efficiency.

6 Factors affecting typing efficiency in CP typists

6.1 Key Distance

We calculated the mean key distance and the mean IKI for each participant to examine whether key distance influences typing speed. As shown in Fig. 5, although CP typists exhibited significantly longer average IKI than non-disabled typists, neither group demonstrated notable differences in typing speed across varying key distances. In other words, the correlation between key distance and typing speed was very weak, suggesting that differences in typing efficiency are not primarily determined by physical key span, but are more likely related to motor control and visual strategies.

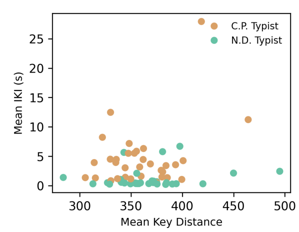


Figure 5: Relationship between Mean Key Distance and IKI

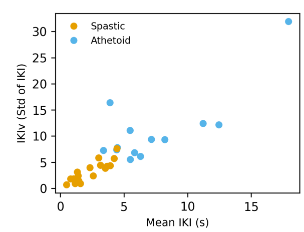


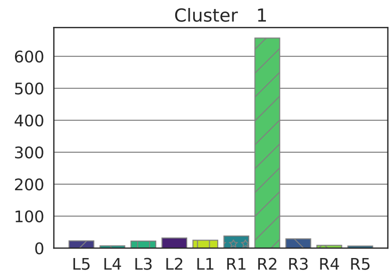
Figure 6: Relationship between CP Subtypes and IKI

6.2 Clustering of Movement Strategies

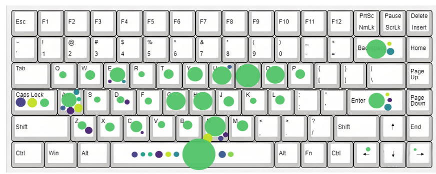
We aim to investigate whether CP typists exhibit certain similarities in their typing patterns. To achieve this, we record the proportion of each finger used by participants when pressing each of the 77 keys on a keyboard, representing this as a 10-dimensional proportion vector $\mathbf{p}$, where $\sum_{i=1}^{10} p_i = 1$. Subsequently, we aggregate these proportion vectors across all 77 keys into a single 770-dimensional vector that characterizes the typing features of each participant. Finally, we employ a hierarchical clustering algorithm on these feature vectors, utilizing the Ward linkage method [21] as the clustering criterion.

Clustering results are shown in Fig. 7. The identified typing strategies are as follows:

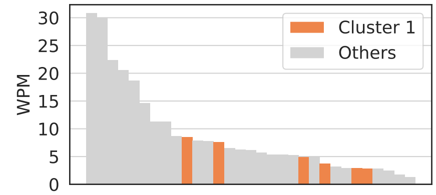
(1) **Right Index Typist (Cluster 1):** Primarily uses only the right index finger for typing, with minimal or no involvement



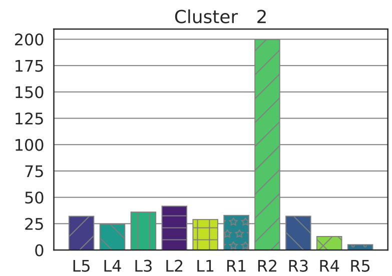
(a) Finger usage pattern



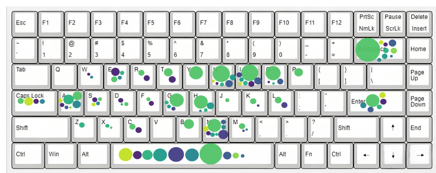
(b) Keyboard Mapping of Cluster 1



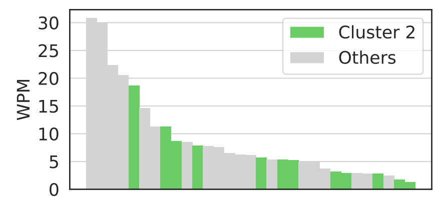
(c) Distribution of WPM for Cluster 1



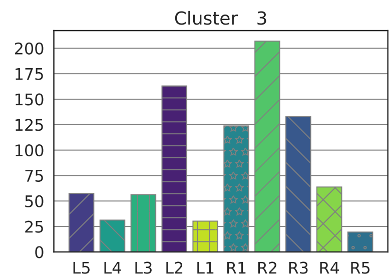
(d) Finger usage pattern



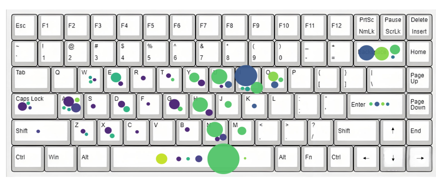
(e) Keyboard Mapping of Cluster 2



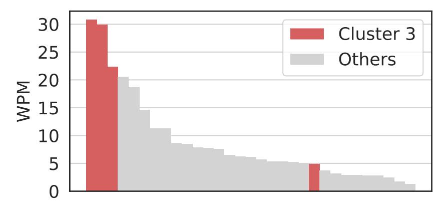
(f) Distribution of WPM for Cluster 2



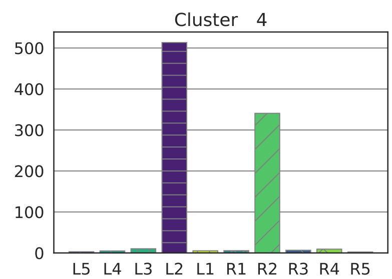
(g) Finger usage pattern



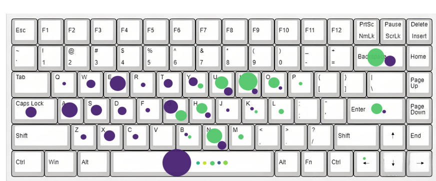
(h) Keyboard Mapping of Cluster 3



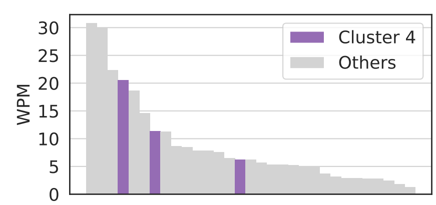
(i) Distribution of WPM for Cluster 3



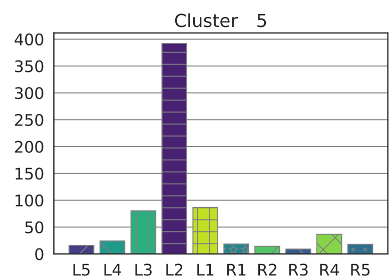
(j) Finger usage pattern



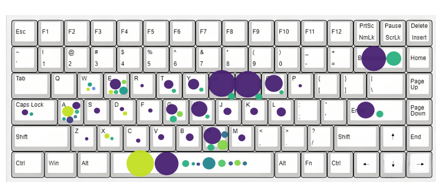
(k) Keyboard Mapping of Cluster 4



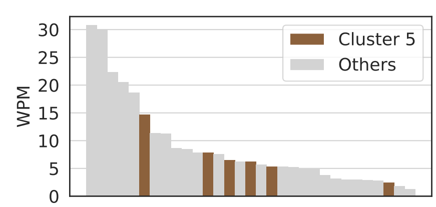
(l) Distribution of WPM for Cluster 4



(m) Finger usage pattern



(n) Keyboard Mapping of Cluster 5



(o) Distribution of WPM for Cluster 5

Figure 7: Clustering results of CP typists' finger-to-key mappings. Each row shows a distinct typing strategy. Larger circles on the keyboard indicate higher keypress frequency; L5–L1 denote left little finger to left thumb, and R1–R5 denote right thumb to right little finger.

of other fingers. These typists achieve an average WPM of 5.09. Occasional use of other fingers is concentrated on functional keys such as Caps Lock for switching case, the Spacebar, Enter, and Backspace. Additionally, the "A" and "N" keys see some use of other fingers.

(2) **Right-Dominant Index Typist (Cluster 2):** Mainly uses the right index finger for typing, with limited use of other fingers compared to the Right Index Typists. The average WPM for these typists is 6.24. Other fingers are noticeably more involved on the left side of the keyboard, and functional keys are frequently operated with other fingers.
(3) **Full-Finger Typist (Cluster 3):** Utilizes all fingers for typing, though the index fingers on both hands have the highest usage frequency. These typists have an average WPM of 22.00. Notably, the right middle finger is primarily responsible for inputting the "I" key.
(4) **Dual Index Typist (Cluster 4):** Relies exclusively on the index fingers of both hands for typing, with minimal or no use of other fingers. The average WPM for these typists is 12.72. The use of the left and right index fingers is roughly divided along the keys "Y," "U," "G," "H," "B," and "N."
(5) **Left Index Typist (Cluster 5):** Primarily uses the left index finger for typing, with other fingers rarely engaged. These typists achieve an average WPM of 7.16. Other fingers are mainly responsible for functional keys. It is noteworthy that the thumb is often used for pressing the Spacebar and the "A" key.

6.3 Subtypes of CP

Our study selected and distinguished two subtypes of CP participants, namely spastic and athetoid. As shown in Fig. 6, the two subtypes exhibited significant differences in typing behavior. Spastic typists had longer average inter-key intervals, resulting in slower overall speed, but their keystroke rhythm was relatively stable, reflecting a "slow but steady" pattern. In contrast, athetoid typists showed greater variability in typing speed and markedly unstable rhythms, reflecting a "fast but unstable" pattern.

6.4 Other factors

We created a questionnaire for participants to self-report their disability level. For details, please refer to the appendix.

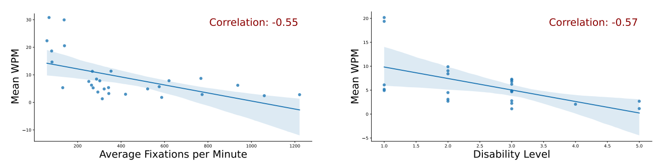
Table 2 illustrates the insights into the factors affecting typing efficiency in CP typists. We categorized the metrics into eye gaze, and disability level, and assessed their impact using a correlation index represented by symbols ranging from * to ***.

The results indicate that average fixations per minute have a moderate correlation with typing efficiency, as illustrated in Fig. 8a. In contrast, average fixation duration and the proportions of keyboard focus and ineffective time show minimal to negligible correlations.

Factors like finger mobility, finger flexion ability, and simultaneous finger extension show moderate correlations. In contrast, metrics like resisted grip strength, tremor, and dysmetria have lower correlations.

	Metrics		Correlation Index
Eye Gaze	Average Fixations per Minute	**	-0.55
	Average Fixation Duration(ms)	*	0.22
	Proportion of Keyboard		-0.02
	Proportion of Ineffective Time		-0.07
Disability Level	Finger Mobility	**	-0.57
	Finger Flexion Ability	**	-0.40
	Simultaneous Finger Extension	**	-0.47
	Resisted Grip Strength		-0.10
	Thumb Adduction	**	-0.44
	Grasp a Cylindrical Object	**	-0.49
	Tremor	*	-0.32
	Dysmetria		-0.18

Table 2: Factors Affecting Typing Efficiency in CP Typists. This table presents various metrics related to eye gaze, disability level, and their corresponding correlation indices with typing efficiency. The strength of the correlation is represented by symbols ranging from * to *: * indicates a low correlation, ** indicates a moderate correlation, and *** indicates a high correlation.**



(a) Correlation between average fixations per minute and WPM

(b) Correlation between disability level and WPM

Figure 8: Correlations of two factors with WPM.

6.5 Discussion

The varying WPM across different typist categories provides valuable insights into typing efficiency and strategies among CP typists. Typists who rely solely on a single finger, such as the right index finger, demonstrate a slower typing speed, reflecting a less efficient approach due to the limited number of fingers involved. Conversely, those who primarily use one finger but incorporate minimal use of others achieve a slightly higher speed, indicating that even limited additional finger use can enhance typing efficiency. Typists employing a full-finger strategy, making extensive use of all fingers, exhibit a significant improvement in typing speed, highlighting the efficiency gained by distributing typing tasks more evenly across multiple fingers. Notably, typists who use both index fingers or focus on one hand show improved speeds compared to single-finger typists but still lag behind those using all fingers. These findings suggest that typing speed improves as the number of fingers used increases, with a full-finger strategy proving to be the most efficient.

While the general trend shows that more fingers lead to faster typing, many CP typists are constrained by their motor control abilities. Among these constraints, finger mobility stands out as a particularly critical factor. Enhanced finger mobility allows for more precise and varied finger movements, which directly contribute to better typing efficiency. Additionally, finger flexion ability and the capacity for simultaneous finger extension play essential roles in enabling smoother and more coordinated keystrokes. The moderate correlations observed between these metrics and typing efficiency underscore the importance of focusing on improving finger mobility and flexibility. These findings highlight the need for tailored interventions and assistive technologies that prioritize the development of finger mobility and dexterity, helping CP typists optimize their typing strategies within the limits of their motor capabilities.

Our results further reveal differences in typing behaviors between CP subtypes. Spastic typists were characterized by slower speeds but more stable rhythms, which is consistent with their clinical features of increased muscle tone and restricted movements. In contrast, athetoid typists exhibited greater variability in speed and more pronounced rhythm fluctuations, likely stemming from frequent involuntary movements and difficulties with postural control. This contrast of "slow but steady" versus "fast but unstable" highlights the profound influence of underlying motor impairments on input patterns. These findings not only deepen our understanding of the mechanisms underlying typing behaviors across CP subtypes but also provide implications for the design of assistive technologies. For spastic typists, interventions should focus on reducing keystroke latency and enhancing overall typing speed; whereas for athetoid typists, the priority should be on improving rhythm stability and reducing error rates. Future assistive input technologies tailored to the specific characteristics of each CP subtype may thus more effectively enhance typing experience and efficiency.

Regarding other influencing factors, the results indicate that average fixations per minute have a moderate correlation with typing efficiency, suggesting that the frequency of visual attention plays an important role in typing performance. A higher fixation frequency may reflect more flexible visual scanning and confirmation abilities, thereby supporting more efficient input. In contrast, average fixation duration, the proportion of keyboard focus, and ineffective fixation time show weak correlations with typing efficiency, implying that the typing performance of CP typists relies less on the allocation of gaze time and more on the ability to shift and maintain visual attention. In terms of motor factors, finger mobility, finger flexion ability, and simultaneous finger extension demonstrate moderate correlations with typing efficiency, underscoring the importance of fine motor control for smooth and efficient keystrokes. Improvements in these abilities contribute to more coordinated and effective typing. By comparison, resisted grip strength, tremor, and dysmetria exhibit weaker correlations, suggesting their limited influence on typing efficiency. Overall, these findings highlight the key constraints in typing performance among CP typists: the frequency of gaze shifts and finger mobility. Future interventions and assistive technology design should focus on improving eye movement control and finger dexterity, rather than merely increasing strength or prolonging fixation time. Such targeted approaches may provide more effective support and significantly enhance typing efficiency for individuals with CP.

7 General Discussion

7.1 Design Implications

In the HCI and ASSETS communities, a wide range of assistive input technologies have been proposed to improve typing efficiency for individuals with motor impairments. Our findings further indicate that CP users are not merely passive typists constrained by motor limitations, but actively regulate their typing behavior by adjusting speed, attentional allocation, and movement rhythms to maintain controllability and stability under long-term motor uncertainty. This suggests that the design goals of assistive systems should not be limited to optimizing objective performance metrics alone, but should also support users' self-regulation mechanisms and strategy construction processes.

For example, the TrueKeys system [11] improves typing accuracy through automatic error correction, often at the cost of reduced typing speed. Similarly, we found that although CP users type more slowly overall, their keyboard efficiency is comparable to that of non-disabled users. This may be attributed to the high cost of error correction, which encourages CP users to adopt more cautious strategies during initial input in order to minimize errors. This indicates that, in the context of CP typing, the trade-off between speed and accuracy is not a deficiency, but rather a reasonable and adaptive self-regulation outcome.

Based on these findings, we derive the following design implications:

(1) The relatively high rate of ineffective keystrokes (UER) and slower typing speed of CP users suggest that incorporating real-time next-letter prediction and automatic correction mechanisms could improve overall input efficiency without compromising accuracy.
(2) Eye-tracking data show that CP users generate approximately 125 fixations per minute (compared to 78 for non-disabled users), with shorter fixation durations and about 32% of time spent looking at the keyboard, indicating a highly monitored input mode. To reduce visual load, interface designs could incorporate dynamic key highlighting, salient visual cues, or finger projection overlays to minimize frequent gaze switching.
(3) CP users commonly exhibit limited and uneven finger usage, primarily relying on the index finger for input. This suggests that assistive systems could map high-frequency keys to more easily operable finger regions and dynamically adjust key sizes based on actual usage patterns, thereby improving efficiency and reducing motor burden.
(4) Clear differences in rhythmic characteristics are observed across CP subtypes: spastic users exhibit a "slow but stable" rhythm, whereas athetoid users display a "faster but unstable" pattern. Therefore, assistive systems should provide subtype-sensitive support strategies, such as prioritizing rhythm stabilization and error suppression for athetoid users, and reducing keystroke latency to increase speed for spastic users.

7.2 Limitations

This study has several limitations. First, the experimental tasks were limited, and no stratified analysis was conducted for different ages or severity levels, which may affect typing strategies and efficiency. Second, the experiment did not integrate modern keyboard features, such as word prediction and auto-completion, which have been shown to improve input efficiency by about 30% for non-disabled users [3] and may offer even greater benefits for CP users. Third, only desktop physical keyboards were tested; touch keyboards or multimodal inputs (eye tracking, gestures, voice) may be more suitable for CP users.

7.3 Future Work

Our findings provide several promising directions for future research in the HCI and ASSETS communities. First, given the substantial and continuous gaze-switching demands between the screen and the physical keyboard experienced by CP users, future work could explore interaction designs that integrate the keyboard and text display into a unified visual space. For example, overlaying simplified finger contours, contact points, or localized key regions directly onto the screen could allow users to maintain a single visual focus during input, thereby reducing visual–motor coordination costs. Future studies could systematically compare different projection styles (e.g., static outlines, dynamic motion trajectories, adjustable transparency, or active finger indicators) and examine their effects on gaze distribution, rhythmic stability, and visual load.

Second, considering the potential advantages of virtual keyboards in spatial alignment and visual integration, future research could further investigate how CP users type on touch-based, virtual reality (VR), or augmented reality (AR) keyboards. Such studies could analyze compensatory strategies in virtual environments, such as avoidance trajectories, force modulation, or rhythm adjustments. Building on these insights, future work could develop adaptive virtual keyboards that integrate character prediction and dynamic key-size adjustment to reduce input costs caused by limited movement ranges.

Finally, future research could adopt broader multimodal and longitudinal perspectives by systematically exploring combinations of touch, eye tracking, speech, gesture, and keyboard input, in order to identify optimal modality configurations for users with diverse motor and visual abilities. Longitudinal studies could further reveal learning curves, fatigue accumulation, strategy evolution, and interface adaptation mechanisms over extended periods of use. Such findings would provide theoretical foundations for building personalized assistive input systems that dynamically adjust prediction logic, key layouts, and guidance feedback over time, enabling more robust, sustainable, and ecologically valid accessibility solutions in real-world contexts.

8 Conclusion

This study presents a comprehensive investigation of typing behaviors in individuals with CP through an integrated analysis of typing performance, eye-tracking data, and finger usage patterns. Our results reveal that CP typists exhibit significantly slower speeds, longer and more variable inter-key intervals, and higher error rates than non-disabled typists, while their overall keyboard efficiency remains comparable—reflecting a tendency to prioritize accuracy over speed. Eye-tracking results further highlight distinct visual strategies in CP typists, characterized by shorter and more frequent fixations, greater reliance on the keyboard, and more frequent gaze shifts. In terms of motor performance, CP typists demonstrate limited finger usage and distinct finger-based strategies, ranging from single-finger reliance to more distributed full-finger input. We also identified five major typing strategies and observed clear differences between CP subtypes: spastic typists adopt a "slow but steady" rhythm, whereas athetoid typists display a "fast but unstable" pattern.

These findings deepen our understanding of how motor and visual impairments jointly shape the input behaviors of individuals with CP, and emphasize the need for personalized assistive technologies. The proposed metrics, including IKI variability, fixation dynamics, and finger clustering, not only provide richer insights into typing efficiency but also hold potential clinical value as objective indicators of motor control and visual strategies. Future research should expand testing scenarios by incorporating modern keyboard features (e.g., prediction and auto-completion), touchscreen environments, and longitudinal studies of training and fatigue effects, thereby advancing both the design of adaptive input systems and the clinical evaluation of rehabilitation outcomes for people with CP.

Acknowledgments

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