

How We Type: Movement Strategies and Performance in Everyday Typing

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Figure 1. Four users showing different typing behaviours involving different numbers of fingers and movement strategies. This paper reports typing rates, gaze and movement strategies for everyday typists, including both professionally trained and self-taught typists. We explain how untrained typists are able to type at very high rates, which were previously attributed only to the touch typing system that enforces the use of all 10 fingers.

ABSTRACT

This paper revisits the present understanding of typing, which originates mostly from studies of trained typists using the ten-finger touch typing system. Our goal is to characterise the majority of present-day users who are untrained and employ diverse, self-taught techniques. In a transcription task, we compare self-taught typists and those that took a touch typing course. We report several differences in performance, gaze deployment and movement strategies. The most surprising finding is that self-taught typists can achieve performance levels comparable with touch typists, even when using fewer fingers. Motion capture data exposes 3 predictors of high performance: 1) unambiguous mapping (a letter is consistently pressed by the same finger), 2) active preparation of upcoming keystrokes, and 3) minimal global hand motion. We release an extensive dataset on everyday typing behavior.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords

Text entry; typing performance; touch typing; movement strategies; motion capture data

INTRODUCTION

This paper revisits present-day understanding of one of the most prevalent activities in computer use: typing. We are concerned that the current understanding mostly originates from an era when typing was much more homogenous than today.

Studies were carried out with trained typists (e.g., [2, 4, 6, 8, 23, 27, 29]) mostly operating typewriters. The participants were often professionally employed typists, skilled in typing with 10 fingers and able to consistently perform at rates of over 80 words per minute (wpm) [8, 22, 24].

We are seeking to shed new light on the everyday typing techniques, employed by a majority of users, that do not fall within the *touch typing system*. Touch typing originates from the 1890s and is the technique taught in typing classes. Column-wise, each key is assigned to one finger. Each finger has a home position in the middle row to which it returns after pressing a key. Finger travel movements are small, which decreases inter-key intervals. Touch typists practice these movements to enter text without having to look at the keyboard. While the system can be learned rather quickly, it requires deliberate training of hundreds of hours [26, 35] to reach performance rates reported in literature. As a result, billions of computer users today are not skilled in touch typing.

The present study characterises the movement and performance of present-day computer users, hereinafter called *everyday typists*. A recent study of typing performance in undergraduate students [17] showed average rates of only 33 net wpm, far removed from the figures reported in older studies. Also, modern keyboards are flatter, and their keys have a shorter travel distance than typewriters. The characteristics of the typed text vary widely: from the formal language of essays and reports, to the abbreviations used in chat programs and social networks, or different languages entirely. Moreover, the keyboard is used for many more tasks, such as gaming and programming. Such factors may give rise to typing techniques driven by other objectives. Thus, while we know much about the keystroke performance and cognitive aspects of trained typists, we know barely anything about the everyday typist who may use anything between “two finger hunt-and-peck” and touch typing. Figure 1 shows four examples of variable techniques employed by participants in our study.

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We study transcription typing using modern motion tracking technology. This addresses the challenge that finger articulations in typing are very rapid and complex by nature. Several fingers are moving simultaneously with inter-key intervals on the order of a few hundred milliseconds. When asked to report their strategies, users are usually unable to adequately describe them. “It just happens.” Motion tracking technology is able to record exact movements at very high rates and was recently used to analyze similar high performance tasks, such as the movement dynamics in piano playing [10, 19]. We obtain millimeter-accuracy 3D positions of hands and fingers at and between each key press. In this way we can explain differences in typing rates by reference to motor behaviour.

We report on a study with 30 everyday typists, selected to span a wide range of typing performance (from 34 to 79 wpm) and age (from 20 to 55 years), as well as two languages. We describe first observations on performance and movement characteristics. In this paper, we concentrate on motor aspects related to performance, as well as on visual attention and gaze deployment.

Surprisingly, we find that regardless of the number of fingers involved, an everyday typist may achieve entry rates over 70 wpm. Even some participants using only 1 or 2 fingers per hand can achieve a level of performance normally attributed to touch typists. This contradicts the common belief that everyday techniques are inferior and exhibit slow or disorganised movement strategies. In fact, our analysis revealed only few differences between trained touch typists and those without formal training, including the amount of time spent looking at the keyboard and the average number of fingers used. As expected, the largest difference was in the typing technique itself. By using hierarchical clustering on the finger-to-key mappings, we find 4 clusters for the left and 6 clusters for the right hand that characterise the typing techniques that people use. They range from easy one finger input with the index or middle finger, to multi-finger techniques, such as touch typing. Each cluster shows a broad range of input rates, ranging from less than 50 to over 70 wpm.

A closer analysis of motion data allowed us to conclude that everyday typing techniques can be fast if motor behaviour is organised in a particular way. We identified three predictors for high performance: 1) unambiguous finger-to-key mapping, such that a letter is consistently pressed by the same finger; 2) preparation of upcoming keystrokes; and 3) reduced global hand motion.

These findings encourage more studies to refine our understanding of typing. The results may be useful for optimisation of keyboard layouts, adaptive and personalised assistive input, and the design of input methods that leverage the expertise of users. We note that the fastest typists in our study were typically *not* touch typists. Analyzing the commonalities in their movement strategies could potentially devise a typing technique superior to the touch typing system.

The HOW-WE-TYPE dataset will be made publicly available to support further research on this important topic.

RELATED WORK: STUDIES OF TYPING

For nearly a century, researchers have made efforts to understand cognitive and motor aspects of typing. However, the achieved understanding is based on professionally trained touch typists. We briefly review these main findings and summarise key points for comparison in our study. We then discuss a few more recent studies looking at other typing techniques on physical keyboards and multitouch devices.

Phenomena of Touch Typing

Until the introduction of personal computers, expertise in text entry implied being a professionally trained touch typist. Studies by Salthouse [23], Gentner [7, 8, 9] and Shaffer [27, 28] from the 1970s and 80s were conducted exclusively with professionally trained touch typists, or typists in different stages of touch typing courses. Almost all were female. As touch typists, their finger-to-key mappings were clearly defined. Thus, recording the interval between two key presses was enough to characterise the typing behavior and make conclusions about performances of hands and fingers. Inter-key intervals and typing speeds were analyzed either by video recordings, time keepers or computational logs. Studies were performed on typewriters, both electrical and mechanical, or computer keyboards of this era.

The findings accumulated over numerous studies during this time are reviewed for example in [24] and [34]. Table 1 summarizes phenomena and results particularly related to performance and motor behavior. Where possible we reference exact numbers for each measure. We note that the table omits many known phenomena related to cognitive and perceptual processes, such as the eye-hand span or effect of reduced preview. In this study, we focus on the observable aspects of motor control and performance. Moreover, we expand the analysis by motion capture data which is necessary to understand non-touch typists. We look at factors such as global hand motion, anticipatory movement and the finger-to-key mapping, which we found to be predictive of high entry rates.

Theories and Models

One goal of prior research has been to explain the cognitive processes that organise and schedule the perceptual and motor aspects of typing — from parsing the text to performing the corresponding keystrokes. Given a to-be-typed letter sequence, these models try to predict the times between two key presses based on the hand and fingers used for typing, as given by the touch typing system.

The Central Control Model from 1980 [30] suggests that the inter-key intervals (IKI) are a result of word-specific time patterns stored centrally and generated in parallel. The simulation model of Rumelhart and Norman from 1982 [22] assumes that the finger movements are controlled by hierarchically organised motor programs, which are executed based on their activation value. The execution of one program may lead to the increase or decrease of the activation value of another. The simulation reproduces a number of phenomena, such as the benefit of hand alternation and different patterns of errors. The Typist model, proposed in 1996 [15], is built within the framework of the Model Human Processor [3]. It covers 19

Phenomenon or Measure	M	SD	Ref
Background Factors: <i>Studies were usually conducted with professionally trained and employed typists.</i>			
Participants touch typing (%)	100	0	
Weekly amount of typing (h)	11	19	[23]
Performance: <i>Average inter-key interval (IKI) is a fraction of typical choice-reaction times (e.g. 560 ms). The typing rate is slowed for random letter sequences.</i>			
Words per minute	75	9.7	[13]
IKI easy prose (ms)	140	–	[29]
IKI random strings (ms)	326	–	[29]
Hand- and finger alternation: <i>Letter pairs (bigrams) typed by fingers of different hands is 30–60 ms faster than those typed by the same hand.</i>			
Bigrams typed by:			
Hand alternation (%)	48	–	[5]
- IKI (ms)	155	43	[23]
Finger alternation (%)	34	–	[25]
- IKI (ms)	194	45	[23]
Same finger (%)	4.6	–	[5]
- IKI (ms)	223	41	[23]
Letter repetition (%)	n/a	–	
- IKI (ms)	176	26	[23]

Table 1. Well established phenomena and their corresponding measures based on prior studies of professional touch typists. Exact values are selected from the referenced papers and may vary in other studies.

phenomena of transcription typing, most of them reviewed by Salthouse [24]. The more recent Queuing Network Model from 2008 [34] is based on the Queuing Network Model Human Processor [18] which combines mathematical queuing networks and symbolic models of cognition. These simulation models aim to explain the typing phenomena listed by Salthouse and others, with varying levels of success. To our knowledge, the only mathematical model was proposed in 1980 [14]. Based on the typing data of a single professional typist, they proposed a linear model that predicted the inter-key interval as a function of different characteristics of the fingers used to press the keys, such as hand alternation, finger and row transition, as well as the frequency of the letter pair.

To make these models applicable to today’s computer users, we need to extend them to cover self-taught typing techniques. This paper makes a first step towards collecting the necessary data and reports first observations.

Studies of Everyday Typing

Physical keyboards

We could identify only two prior studies investigating non-touch typists entering text on physical keyboards. A study from 2007 [17] reported on the performance of 60 undergraduate students of different typing background. Average input performance was 33 net words per minute (“net wpm” is computed by subtracting 5 characters for each mistake). They found that performance correlates with self-reported deliberate typing practice, where highest entry speed was seen for participants who took a typing course. A study from 2008 [12] assessed the performance of 32 female students not trained in typing. They found that self-taught typists were not as efficient

as the professionally trained touch typists studied by Salthouse. They made more mistakes and required more visual guidance. However, average inter-key intervals within words were as low as 170 ms, despite the lack of deliberate training.

Multitouch devices

More extensive studies of everyday typing were done on touch-screen devices. A recent study compared typing performance on a regular keyboard and tabletop surface [31]. On average, performance was found to be about 60 wpm on a physical, and 30 wpm on the soft keyboard [31]. Input strategies were only observed manually by the experimenter. For typing on the tabletop, they fall into three categories: Hunt-and-Peck, Full-Use, and Hybrid. They reported that all participants employed Full-Use on the physical keyboard. However, it is unclear if this corresponds to the touch typing system. Input strategies, grips and hand postures were also studied for 1–2 finger input on smartphones to develop better models of touch locations, support auto-correction, and adapt the keyboard to users’ behavior [1, 11, 20, 36]. However, this form of input is very different and much more limited than typing on a physical keyboard with global hand motion and 10 end-effectors.

METHOD

We collected typing data in a transcription task with 3 types of materials: easy sentences, random letter strings, and a mix of both. A phrase was presented on the display and should be entered as participants would usually do. We allowed correcting errors to make the task more realistic. Thirty typists participated in the study, spanning a wide range of typing performances, ages, as well as two languages. In addition to key press data, we collected motion capture data of the hands, tracking the position of each finger at and between the keystrokes. Moreover, we capture the switch of attention between the keyboard and screen with eye-tracking glasses. An overview of the setup is given in Figure 2.

Participants

We recruited 30 participants (17 female) ranging in age from 20–55, with a mean of 31. Three participants were left handed. Our participant pool had either Finnish or English as their mother tongue or most commonly used language for typing. In order to observe the over-trained movements used in everyday typing we let participants choose the language they were familiar with (18 Finnish / 12 English). The keyboard was the same for both languages (QWERTY layout with special characters, see Figures 7, 8). Their performance, measured based on the collected data, ranged from 34–79 wpm. All participants reported to have permanent access to a computer either at work or at home. Their self-reported computer experience varied between 6 and 35 years. Participants were rewarded with a movie ticket worth 10€.

Experimental Design

The experiment followed a within-subject design with one independent variable: stimulus type, with three levels: easy sentences with commonly used word (*sentences*), random letter strings (*random*), and a mix of both (*mix*). Their order was randomised throughout.

Materials

For the sentences condition, 50 easy and memorable sentences were chosen from the Enron Mobile Email Dataset [32]. They were translated into Finnish by a native speaker, instructed to use simple, everyday language. For the random condition we randomly sampled 50 6-letter strings from a uniform distribution over the alphabet. In the mix condition the random string was added as an extra word in the middle of the sentence. The stimuli were presented in random order.

Apparatus

The setup consisted of three parts: motion capture, text entry, and eye tracking, all shown in Figure 2. In addition we recorded a reference video of the participants' hands.

Motion capture: The experiment was performed in a motion capture laboratory with no visual or auditory distraction during the task. The position and motion of the fingers was tracked with a motion capture system by Optitrack consisting of 8 cameras, recording at 240 fps. We placed 26 adhesive markers on anatomical landmarks of each hand.

Keyboard logging: The typing software (implemented in Python) showed one stimulus at a time on the display. Performance feedback was given at the end of each condition. The physical keyboard had a Finnish layout, similar to QWERTY (see Figure 7, 8). All keypresses were logged.

Eye tracking: We used eye tracking glasses by SMI (ETG-1.8), recording at 30 Hz, to capture the switch of attention between keyboard and display. 3-point calibration was used to calibrate the glasses. Tracking quality varied depending on participants' expertise and typing style and was infeasible with some corrective glasses. In one case data could not be recorded due to technical issues. However, eye tracking glasses were worn in all cases to ensure the same conditions for each participant.

Procedure

Participants were informed that the purpose of the study was to investigate the hand and finger movements of computer users during text entry. Throughout the experiment they were instructed to type as they would normally do, without paying special attention to speed or accuracy, and to correct errors upon notice by using the backspace key. Errors that were not detected within 1-3 characters could be left uncorrected. Participants could choose the stimulus language between Finnish and English. After attaching the markers, participants were asked to sit comfortably and adjust the position of the keyboard on the table to their liking. They were given a practice text to familiarise with the keyboard and were then explained the three conditions. They were asked to first read through a stimulus, memorise it and then transcribe it. Between the conditions, participants were asked if they wanted to take a break. After the study participants filled a questionnaire asking about demographic factors, their computer experience, their typing skill, and the tasks they perform with the keyboard.



Figure 2. Experimental setup: The typing process of 30 participants was captured using a motion capture system and eye tracking glasses. In addition, keypress timings were logged and a reference video recorded.

DATA ANALYSIS

Our analysis covers well-known typing phenomena discussed in Table 1, as well as more advanced measures that require the analysis of motion capture data, which were not considered in previous work. Unless otherwise stated, measures were computed per participant as an average over all phrases typed in the *sentences* condition. To identify statistical trends holding for both languages, we only considered those letters and letter pairs common to both languages and gave equal weight to each letter, where relevant.

Preprocessing

The goal of the preprocessing was to extend the motion capture and typing logs with the information of which finger executed each keypress. We performed four steps:

1. *Cleaning and smoothing:* The built-in functionalities of OptiTrack's Motive:Body [21] software were used to fill short gaps (up to 10 frames) and smooth the data (fluctuations in the signal up to 10 Hz). From the typing log, we excluded outliers more than 2 SD from the mean inter-key interval. On average this was 4.4 % of the data (maximum 5.9 %).
2. *Offline labeling of markers:* To match the point cloud recorded by the motion capture system with the joints of the fingers we used a nearest neighbor approach after manually labeling the first frame, supported by heuristics based on the underlying hand skeleton.
3. *Transformation to keyboard coordinate system:* To enable comparison between participants, we transformed all tracked position data to the keyboard coordinate system, where the Escape key had position (0, 0, 0).
4. *Identify executing fingers:* Given the pressed key, as well as the time and frame at which the key was pressed, the executing finger was identified as the marker that had the shortest distance to the key at the given frame.

To validate these steps, we randomly sampled one sentence per participant and manually identified the executing fingers. On average, one sentence had 23.2 keypresses and the identification was correct for 98.4 % of them.

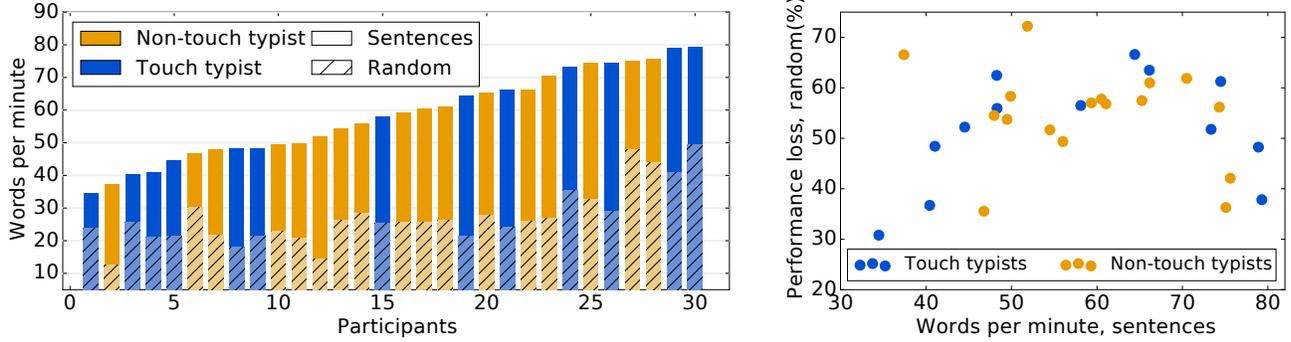


Figure 3. Left: Participants’ performance ranged from 34 to 79 wpm and did not significantly differ between touch- and non-touch typists. Right: The percentage loss in performance when typing random strings was found to be smaller for typists of high skill, trained or untrained.

Typing Performance

We compute the following measure of typing performance for the random and sentences condition:

Words per minute (wpm): based on the raw typing log, without exclusion of outliers. For each sentence we find the time between the first and last keypresses and divide it by the length of the final input given in number of words (any 5 characters).

Inter-key interval (IKI): in milliseconds, average interval between all keystrokes in the preprocessed data, including presses of modifier keys and error correction.

Uncorrected error rate (%): the Damerau-Levenshtein edit distance between the stimulus and entered text and dividing it by the larger number of characters.

Keyboard efficiency: the ratio of number of characters in the input and number of keystrokes. Characterises the accuracy during the typing process. A value close to 0 corresponds to a large number of corrected errors.

In addition we compute the percentage difference in WPM between the two conditions, which further characterises the typing skill of participants.

Eye Gaze

Due to varying tracking quality, analysis was done manually based on the video recordings of the eye tracking glasses.

Gaze shifts: the average number of gaze shifts from the monitor to the keyboard during a sentence.

Visual attention: ratio between the time spent looking at the keyboard and the time a sentence was displayed. Between 0 and 1, where 0 means no time spent looking at the keyboard.

Motion Analysis

In the following analysis we only consider the letters common to both the Finnish and English sentences and exclude control keys, space, and punctuation.

Number of keys: operated by each finger and hand.

Keys per finger: the avg. number of keys mapped to each finger.

Percentage and average IKI of letter pairs (bigrams) typed by:

1. *Hand alternation*: fingers of different hands,
2. *Finger alternation*: different fingers of the same hand,
3. *Same finger*: typing different letters with the same finger,
4. *Letter repetition*: pressing the same key twice.

Entropy of the finger-to-key mapping: the finger-to-key mapping describes which finger a participant uses to press each key. The entropy tells how consistently a key is pressed with the same finger. For each key k , given a frequency distribution over the 10 fingers we compute the entropy as:

$$H_k = - \sum_{f \in \text{Fingers}} p_f \log_2(p_f) \quad (1)$$

where p_f is the probability that finger f presses key k . The average entropy of a finger-to-key mapping is then computed as sum over the entropies of each key weighted by the frequency of the corresponding letter. The touch typing system has 0 entropy, as each key is pressed by only one finger.

Global movement: of each hand, computed at each keypress as the average of the standard deviations of the x -, y - and z -coordinates of the two markers on the back of the hand.

Distance to the next key: the average distance of the executing finger to its target at the time of the preceding keypress. Measures the *preparation* of upcoming keystrokes by moving a finger to to its target during the execution of a preceding keypress.

RESULTS

We collected 93,294 keypresses over the three conditions, and 36,955 in the sentences condition. Results of all statistical tests are summarised in Table 2. It compares participants trained in the touch typing system (hereinafter called *touch typists*) and those that never took a typing course (*non-touch typists*) in several dependent variables. The classification was based on the self-reports of participants. Statistical significance was tested at the 5% level using the the Mann-Whitney signed rank test, as required by the data, which are not normally distributed and have different cell sizes. Where the distribution of the data allowed, we performed a 2-way ANOVA with language and touch/non-touch as factors. However, it showed no effect on any metric, except the reported hours of

weekly typing. Detailed results per participant are provided in the HOW-WE-TYPE dataset.

Background Factors

Based on the survey, 43% of participants learned and used the touch typing system. The average amount of touch typing experience was 17 years ($SD = 9.7$). The mean age of touch typists and non-touch typists was not significantly different. More background factors are shown in Table 2

Performance

Surprisingly, we did not find a significant difference in *input performance* between touch typists and non-touch typists. Average entry rate and IKI were found to be 57.8 WPM and 176.39 ms for touch typists, and 58.93 WPM and 168.91 ms for non-touch typists. The performance in wpm of each participant is shown in Figure 3. Touch typists and non-touch typists had statistically similar *uncorrected error rates* — measuring errors remaining in the final input — of 0.76 % and 0.47 % for respectively. Both groups typed with high *efficiency*, making few mistakes and requiring few keystrokes to correct them.

The common understanding in the literature was that touch typists could type faster and operate with higher accuracy. However, the presented findings show that touch typists and non-touch typists have comparable speed and efficiency in transcribing sentences.

Effect of random strings

When typing random letter sequences entry rate dropped on average by ~50% compared to the sentences condition. The change was similar across both groups, with no significant difference between their performances in the random condition. The average uncorrected error rate was 0.98 % for touch typists and 0.72 % for non-touch typists, a significant difference. One participant was excluded from this analysis, as the error rate in the random condition was 11%.

Figure 3 shows how the loss of performance changes as typing skill increases. The faster typists can type random material faster, not only in absolute terms but also as a percentage of their typing speed. This can be explained with the findings of Salthouse [23]. He states that high performance text entry cannot only be attributed to well practiced motor patterns corresponding to larger units of language, such as words or phrases. Instead he finds that skilled typists show more consistency in their inter-key interval when typing the same letter repeatedly in the same context. This consistency may still be observed in the random condition.

Eye Gaze

The analysis of eye gaze found that non-touch typists spent a significantly higher amount of time looking at the keyboard, as shown in Figure 4. The average number of gaze switches within a sentence was 0.92 for touch typists and 1.2 for non-touch typists, a significant difference. The ratio of time spent looking at the keyboard was 0.2 for touch typists and 0.41 for non-touch typists, also a significant difference. We found a correlation between the average IKI and eye gaze, as shown in the right plots of Figure 4. Correlation between IKI and gaze switch was 0.81 for touch typists and 0.32 for non-touch

Measure	Touch		Non-Touch		M.-W. Stat.	
	M	SD	M	SD	U	p
Background						
Reported strategy (%)	43.33	—	56.66	—	—	
Years touch typing	16.96	9.66	—	—	—	
Age	33.00	9.15	28.82	7.59	○ 75	0.07
Comp. experience (y)	21.69	7.73	16.38	3.95	○ 64	0.053
Weekly typing (h)	47.15	20.63	44.56	18.39	○ 98	0.44
Performance						
WPM	57.83	15.25	58.93	10.82	○ 103	0.38
- Random	27.43	8.73	27.02	8.46	○ 96	0.28
Avg. IKI (ms)	176.39	44.31	168.91	33.22	○ 103	0.38
- Random (ms)	382.31	122.56	399.36	133.70	○ 100	0.34
Error rate (%)	0.76	0.62	0.47	0.42	○ 82	0.13
- Random (%)	0.98	0.86	0.72	1.08	● 60	0.02
Efficiency	0.88	0.03	0.89	0.04	○ 100	0.34
Eye gaze						
Gaze shift	0.92	0.99	1.20	0.94	● 96	0.03
Visual attention	0.20	0.27	0.41	0.33	● 85	<0.01
Motion Analysis						
#Fingers used	8.54	1.08	6.24	0.94	● 16	<0.01
- Left hand	4.46	0.63	3.47	0.70	● 37	<0.01
- Right hand	4.08	0.73	2.76	0.73	● 23	<0.01
Keys per finger	3.64	0.74	5.65	1.51	● 16	<0.01
- pres. by both hands	1.15	1.17	4.41	2.35	● 24	<0.01
Hand alternation (%)	46.50	0.61	48.26	2.35	● 50	<0.01
- IKI (ms)	150.64	31.78	141.28	32.53	○ 90	0.2
Finger alternation (%)	35.94	6.08	26.42	10.76	● 44	<0.01
- IKI (ms)	161.61	31.66	161.10	41.38	○ 99	0.32
Same finger (%)	11.05	5.88	18.67	9.87	● 50	<0.01
- IKI (ms)	194.90	26.60	202.75	34.24	○ 98	0.31
Letter repetition (%)	6.71	0.10	6.68	0.12	○ 91	0.2
- IKI (ms)	159.30	25.36	145.16	12.59	○ 72	0.06
Hand alt. benefit (ms)	16.96	15.83	28.72	23.48	○ 82	0.12
Entropy	0.26	0.18	0.38	0.20	● 71	0.047
Global mov. left (cm)	0.02	0.06	0.01	0.01	○ 110	0.50
Global mov. right (cm)	1.05	0.80	0.81	0.38	○ 104	0.40
Dist. to next key (cm)	1.94	0.41	2.41	0.59	● 60	0.02

● : Significant difference ○ : No significant difference

Table 2. Overview of results, comparing touch- and non-touch typists. Statistical significance is tested at the 5% level using the Mann-Whitney signed rank test and reported in the last two columns.

typists. For visual attention the correlation was 0.69 for touch typists and 0.53 for non-touch typists.

Although touch typing is not necessarily faster, it allows maintaining visual attention on the display. Often self-taught typists, even fast ones with unambiguous mappings, are more reliant on visual attention to the keyboard. However, the trend lines in Figure 4 indicate that IKI of touch typists increases more rapidly as visual attention increases, whereas non-touch typists can maintain high performance under gaze switches.

Motion Analysis

Hand and finger usage

Somewhat unsurprisingly, touch typists use more fingers than non-touch typists (8.5 vs. 6.2). As a consequence, a non-touch typist needs to operate more keys per finger than touch-typists (3.6 vs. 5.6). Touch typists have a clear separation between left and right hand, whereas for non-touch typists there are more keys that fingers of *both* hands operate. All participants used significantly more fingers of the left than of the right hand. In the Section *Clustering of Movement Strategies* we report on the differences of hand- and finger usage in more detail by clustering the finger-to-key mappings.

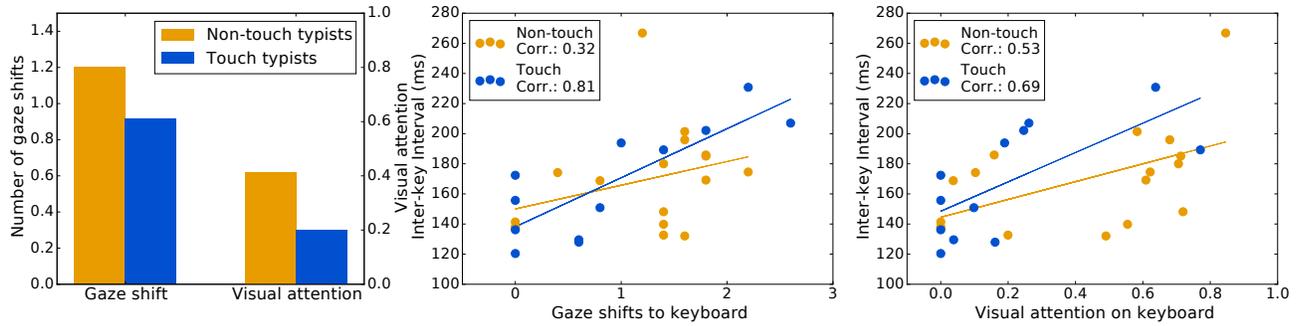


Figure 4. Characteristics of eye gaze during text input. Left: Touch typists spent less time looking at the keyboard (visual attention) and required less gaze shift. Right: Gaze switches and visual attention correlate with the average inter-key interval, increasing as performance gets slower.

Hand and finger alternation

Touch typists enter significantly more bigrams with different fingers of the same hand, whereas non-touch typists prefer to use the same finger for successive keystrokes. However, non-touch typists were found to enter significantly more bigrams by hand alternation and typed them faster than when using fingers of the same hand. On average two letters were typed with an IKI of 141.28 ($SD = 32.53$) when using hand alternation and 170 ms ($SD = 34.53$) otherwise, a significant difference of 29 ms ($U = 72, p = 0.01$). In contrast, touch typists entered bigrams by hand alternation with an IKI of 150.64 ms ($SD = 31.78$), and 167.6 ms ($SD = 28.61$) otherwise, a non-significant difference of 17 ms ($U = 55, p = 0.07$). The distributions of bigrams typed by hand alternation, finger alternation, the same finger, and number of letter repetitions are shown in Figure 5 along with their average IKI. Corresponding numbers are given in Table 2.

Entropy of the finger-to-key mapping

On average, we found that non-touch typists showed more variation in their finger-to-key mapping, which means that a certain key was pressed by different fingers in different contexts. The average entropy for touch-typists was 0.26 versus 0.38 for non-touch typists, a statistically significant difference. However, across both strategies we found that the entropy correlated with performance, as shown in Figure 6(a).

Preparation of upcoming key presses

We found that on average touch-typists better prepare upcoming keystrokes. The average distance of the executing finger to

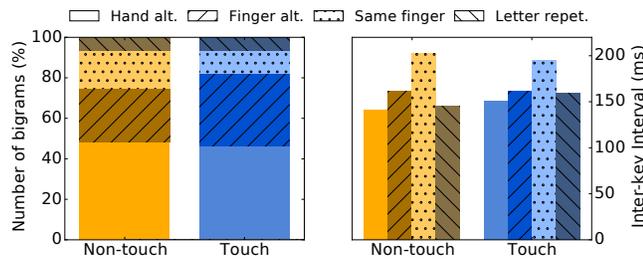


Figure 5. Distribution and average IKI of bigrams typed by hand and finger alternation, the same finger, or letter repetition. Touch typists enter more bigrams by using different fingers of the same hand, whereas non-touch typists more often use the same finger.

its target at the time of the preceding keystroke was 1.94 cm for touch typists and 2.41 cm for non-touch typists. The difference is significant. As shown in Figure 6(b), the preparation of keystrokes correlates with the average IKI.

Global movement of the hands

The deviation from home position measures how much the typist globally moves the full hand to reach a key as opposed to individually moving a single finger. We found that the right hand moves significantly more than the left hand for both touch typists and non-touch typists, as shown in Figure 6(c). The Figure also shows that the global hand motion is a predictor for the average IKI in both left and right hand, and for both touch- and non-touch typists.

Inspection of the reference videos confirmed that both touch- and non-touch typists keep their left hand static in relation to some home position. In contrast, for most people, the right hand does not show such a home position, but instead at the execution of a keystroke, all fingers are moved towards the target. Interestingly, this was also the case for left handed participants. Only highly skilled typists could also keep a static home position in the right hand.

CLUSTERING OF MOVEMENT STRATEGIES

To identify similarities among typists, we performed hierarchical clustering on the finger-to-key mappings of each user. Clustering in this space groups users with similar mappings, revealing the *input strategies* used by multiple users. As described above, we found notable differences in behaviour between the left and right hands — the right hand has higher global movement, while the left hand typically has more active fingers, independent of the handedness of the participant. Given these differences, we decided to cluster the finger-to-key mappings for each hand separately to uncover subtle within-hand effects that might be masked in a joint analysis.

Input Data and Clustering Method

For each user, the feature vector consisted of 10 entries per key, giving the proportion of total presses by each finger. We performed Hierarchical Clustering [16] since it is powerful, flexible and makes no assumptions about the distribution of the data. We used a Euclidean distance measure and Ward's linkage criterion [33] to create compact clusters with minimum internal variance.

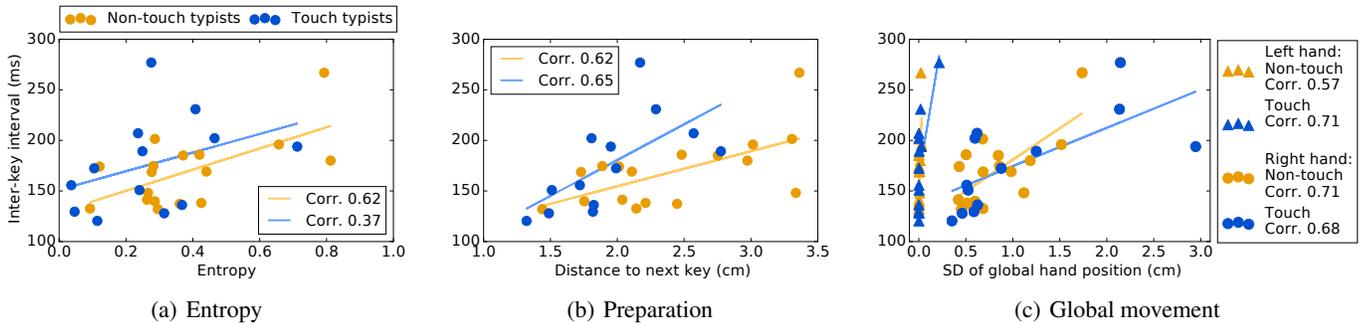


Figure 6. Correlation of inter-key interval with 3 movement characteristics: (a) the entropy of the finger-to-key mapping, (b) the preparation of upcoming keystrokes, given by the average distance of the executing finger from its target at the time of the preceding keystroke, and (c) the standard deviation of the global hand position, given for the left and right hand separately.

In order to avoid biasing the clustering towards effects from the two-language sample, we consider only keys which appear in both the English and Finnish stimuli. This leaves a set of 26 keys (including punctuation and the shift keys) for a total of 260 features in our clustering. Additionally, we do not weight the keys based on their frequency in the data. Thus, the clustering treats all keys equally, even if they were uncommon in the typed phrases.

We obtained the number of clusters by examining the cluster dendrogram and consulting multiple goodness-of-clustering metrics: Dunn index, Davies-Bouldin index, Calinski-Harabasz criterion, silhouette score, and gap criterion.

Results

Following the described approach, we obtained 6 clusters for the right hand and 4 for the left.

Left hand

In the left hand, we found the following 4 strategies:

1. *Index finger typists*: Majority of keys pressed by the index finger. Middle and ring finger may be used for A, S and E, as well as the shift key. $N = 6$.
2. *Middle finger typists*: Majority of keys pressed by the middle finger. Ring finger may press the A, S, E or Shift key. $N = 2$.
3. *Offset touch typists*: Variant of touch typing without the use of little finger, thus shifted by one column to the left. The ring finger handles the A key, and the middle finger the S and E keys. The index finger frequently presses the D key in addition to the touch typing assignment. $N = 7$.
4. *Touch typists*: Finger-to-key mapping closely matches the touch typing scheme. $N = 15$.

Right hand

The right hand displayed more variation. The 6 strategies found by the clustering are as follows:

1. *Index finger typists*: Majority of keys pressed by the index finger. $N = 2$.
2. *Middle finger typists*: Majority of keys pressed by the middle finger. $N = 3$.

3. *Index-dominated two-finger typists*: Primary use of index finger. The middle finger may press keys in the I, O and P columns, as well as backspace. $N = 6$.
4. *Two-finger typists*: Even and spatially strict distribution of keys between the index and middle finger. Ring and little may be used for punctuation, backspace and shift. $N = 7$.
5. *'Lapsed' touch typists*: Similar to touch typing, but keys of the Y and U columns are often typed by middle instead of index finger. Little finger only used for shift. $N = 5$.
6. *Touch typists*: Finger-to-key mapping broadly matches the touch typing scheme, with the exception that little finger may only be used for shift key. $N = 7$.

Observations

There was less variance in strategy in the left hand. Half of our sample had a left hand mapping close to true touch typing, with a further 7 participants using a 3-finger variant. Notably, only 13 participants self-reported as touch typists, so some users have developed similar behaviour independently. By comparison, only 12 of 30 participants consistently used more than two fingers for the letter keys on the right hand.

Within the clusters for both hands, there were small variations in keying behaviour. Even in our touch typing clusters, there were instances where the wrong finger stroked a key. Of the 13 self-reported touch typists, only 3 had a 'perfect' mapping according to the original system.

Supporting our previous findings, the strategies extracted in this way are not predictive of performance. Figures 7 and 8 show fast example users for each cluster and the corresponding performance. Our touch typists ranged in performance from 34 to 79 wpm, while some users who used only 1 or 2 fingers per hand reached speeds in excess of 70 wpm. Thus, if performance is the goal it is not necessarily important which fingers a typist uses, but rather other factors analyzed above, such as consistent finger-to-key mappings, preparation and global hand movement determine the speed. An exception is the middle-finger clusters — no user in either cluster was faster than 55 wpm. It is unclear whether these strategies are suboptimal or our sample was too small to find a fast typist with this behaviour.

Left Hand

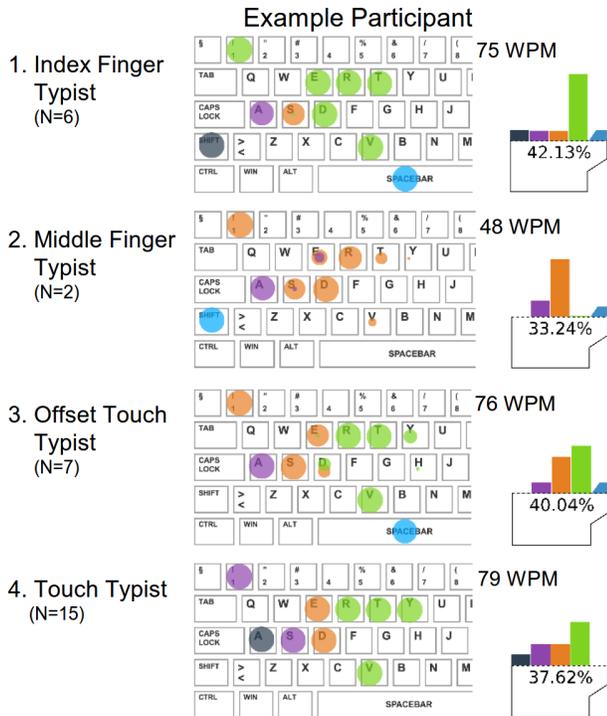


Figure 7. Strategies found by clustering the finger-to-key mappings of the left hand. The figure shows a representative user for each cluster and their average performance. The bar plots show the percentage of keys pressed by the left hand and their distribution over the fingers.

DISCUSSION

This paper has presented an in-depth study of the abilities and idiosyncrasies that characterise everyday typists. Our participants varied in skill, age, experience, and strategies, deploying anywhere from 5 to 10 fingers. The collected dataset is a rich description of their behavior, including finger motions and eye gaze, which to our knowledge have not been looked at in prior studies of typing with computer keyboards. We introduced new metrics to describe their motor behavior based on finger-to-key mapping, global hand motion and preparation of keystrokes.

We have reported the first findings from this dataset, focusing on performance, gaze and movement strategies. Comparing typists trained in the touch typing system and those without any formal training, our main findings are:

- The two groups show no difference in input performance, error rate, or efficiency. Many touch typists are inefficient and many non-touch typists efficient.
- On average, non-touch typists use 6.2 fingers, which is surprisingly close to the 8.5 of touch typists.
- However, even if (some) non-touch typists are fast, this group spends more time looking at the keyboard. In our data, non-touch typists used 40 % of their time looking at the keyboard, whereas touch typists spent only 20 %.
- Touch typists more consistently press a key with the same finger, showing lower entropy in the finger-to-key mapping.

Right Hand

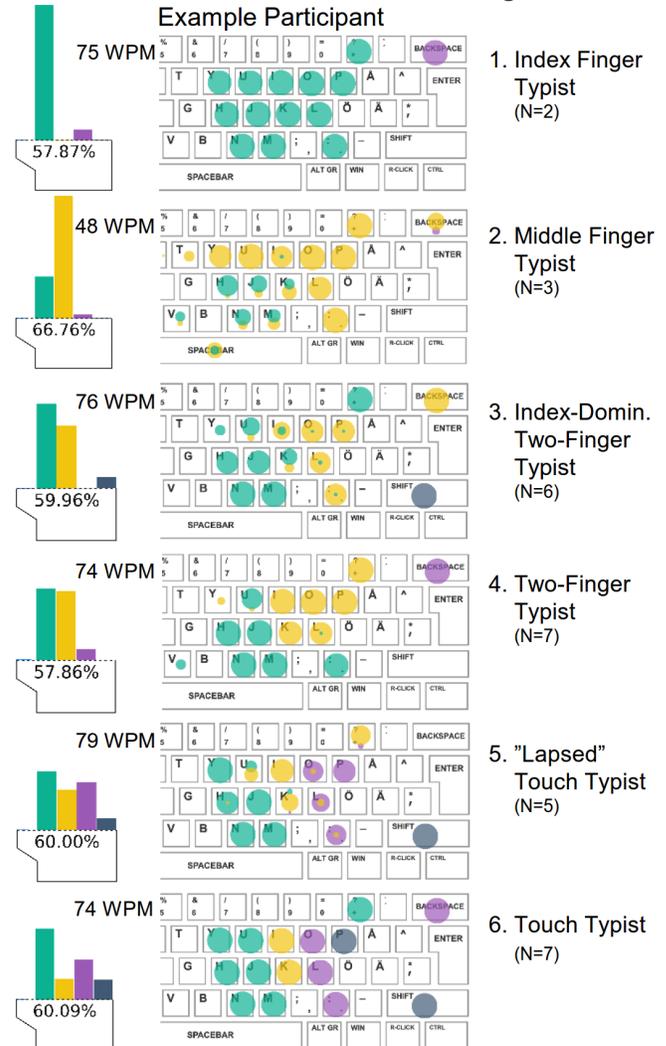


Figure 8. Strategies found by clustering the finger-to-key mappings of the right hand.

- We could not find a hand alternation benefit, as large as previously reported for professional typists. Only the non-touch typists entered bigrams significantly faster by alternating hands than using fingers of the same hand
- Non-touch typists are generally worse at preparing upcoming key presses.
- For both groups, the right hand globally moves significantly more than the left hand.

The most significant discovery is that entering text at high speed does not require mastery of the touch typing system. We have not found this reported earlier in the literature. Figures 7 and 8 show various finger-to-key mappings used by participants. Users of almost all strategies were able to type at speeds over 74 wpm. Thus, in contrast to the common belief, the number of fingers is not an indicator for high performance.

We provide the first explanation for this finding. Our results identified three factors that are predictive of performance:

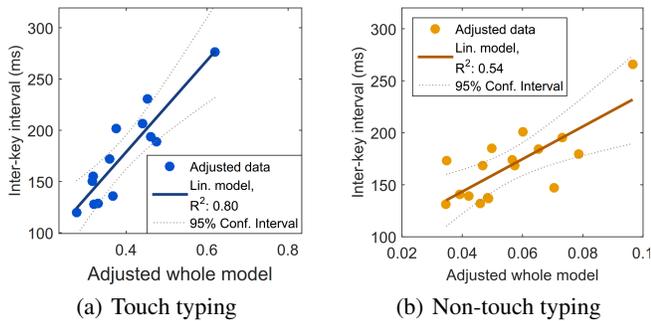


Figure 9. Linear models of performance based on the entropy of the finger-to-key mapping, movement preparation, and global hand motion.

1. *Entropy* of the finger-to-key mapping: faster typists press a key more consistently with the same finger.
2. *Motor preparation*: moving towards the target key already during preceding keystrokes increases performance.
3. *Global hand motion*: slower typists globally move their hands more, while fast typists keep them static.

These three factors correlate with the average inter-key interval and Figure 9 shows a linear model combining them. It predicts typing rates with moderate-to-high fit to our data.

It is somewhat startling to note that efficient keying strategies can emerge in daily use of computers without systematic practice. None of our non-touch typists admitted deliberately practicing typing, yet many achieved entry rates over 70 wpm. By contrast, for touch typists reaching and maintaining a high level of performance (over 70 wpm) requires some form of deliberate practice [17, 35]. Only 3 of our 30 participants stated they deliberately practice typing, and all of them were touch typists. It is interesting to note that while the touch typing system has the potential to be used at a very high speed, when properly trained, none of our participants in this group showed such levels. A self-taught strategy that is consistent in its finger-to-key mapping, and minimises global hand motion, may be easier to acquire and maintain. However, we note that non-touch typists were uniformly worse in terms of gaze deployment. They have to look at the keyboard to guide their fingers. Thus the self-taught techniques may be worse in interactive tasks that require attention to the display.

Hand alternation benefit has been one of the most widely recognised phenomena also for other input methods, but never studied with non-professional typists and modern computer keyboards. Prior research reported benefits of 30–60 ms [24]. In contrast, the difference we found in this study was below this range and, more surprisingly, not found to be significant for touch typists. One explanation may be that today’s computer keyboards have different physical properties than typewriters and keyboards from before the 1990s. The keys require less force to be pressed, the activation point is higher, and the rows of the keyboard are at similar height level. This reduces the travel distance and makes preparation easier from a biomechanical perspective. As a consequence, fingers of the same hand may be able to prepare upcoming keystrokes as well as the fingers of the alternate hand, such that the benefit vanishes. We call on further research to confirm this analysis.

There are many further analyses that could be carried out with this data. For example, our results focused mostly on data from proper sentences — there may be other findings of interest in the random or mixed conditions. The motion capture data also offers exciting opportunities. For example, preparatory movements could be investigated in more detail to understand how optimally and how much in advance non-touch typists prepare movements. Further analysis could also investigate the dynamics between the use of gaze and movement of hands, in particular of non-touch typists. Generally, the combination of motion capture and eye-tracking data provides unique insights into the eye-hand coordination when typing.

CONCLUSION

This paper has shown that – in contrast to the common belief – everyday computer users employing self-taught typing techniques can perform at similar speeds to touch typists. Our investigation of this finding suggests that more important than the number of fingers is the organisation of motor behavior. Fast non-touch typists have an unambiguous division of labour among the fingers. This may minimise uncertainty over which finger presses which key, reducing the need for visual attention and choice. Fast non-touch typists also move their hands and fingers more actively in preparation for upcoming key presses. Most intriguingly, they may be able to obtain this motor behavior without engaging in a systematic training regime. Many of the fastest typists we observed had no formal training in typing. Instead, their input strategies have evolved with the various tasks they perform, such as gaming, chatting, or programming. These observations call for more research to revise our understanding of the motor and perceptual aspects of everyday typing.

THE HOW-WE-TYPE DATASET

The outcome of our study is a unique dataset characterising the performance and behaviour of everyday typists. We are publicly releasing over 150GB of data, which includes:

1. **Motion capture data**: x - y - z coordinates of 52 markers recorded at 240 fps.
2. **Keypress data**: key symbol, press and release time, and inter-key interval for every keypress
3. **Eye tracking data**: 30 fps eye tracking video annotated with gaze points. Derived variables: # of gaze shifts and time spent looking at keyboard.
4. **Performance measures**: classical text entry measures — entry rate, average IKI, error rate and keypress efficiency.
5. **Motion analysis**: motion derived features — finger usage, hand alternation, entropy of finger-to-key mapping, global hand movements, preparation of movements.
6. **Reference video**: video of the hands as they type.

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