EXPERTISE IN TYPEWRITING

Donald R. Gentner

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Expertise in Typewriting

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**ABSTRACT (Continue on reverse side if necessary and identify by block number)**

OVER
Abstract

Expert typists have acquired a highly practiced motor skill. A typical professional typist has accumulated over 10,000 hours of practice. Expert typists are much faster than novices, but in addition, their performance is qualitatively different in many ways from novice performance.

During acquisition of typing skill, there is a general shift from cognitive to motor limits on performance. Expert typing is characterized by parallel mental processes that overlap in time, overlapped hand and finger movements, a decreased load on conscious cognitive resources, and reduced variability of the interstroke intervals.

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Introduction

The other chapters in this book are concerned primarily with expertise in mental tasks. Even though an expert waiter or radiologist may use motor skills such as speech and handwriting, the motor skills are not of direct interest to most investigators. This chapter, on the other hand, is concerned with the acquisition and performance of the motor skill of typewriting. Motor skills hold an intrinsic psychological interest because they are the direct, concrete product of the large amount of mental processing required for the planning, coordination and control of actions. From a practical standpoint, motor skills offer a unique advantage to the scientist studying expertise. Most of the interesting events in mental skills go on inside the head and are hidden from our view. The scientist must make indirect inferences about these mental events from data such as reaction times and verbal protocols. In contrast, the normal performance of a motor skill produces an externally observable sequence of events that are directly related to the task.

It is clear from anatomical studies of the brain and observation of patients with brain injury that, even in humans, a large portion of the brain is involved in the performance of motor skills. Some motor skills, such as walking and speech, develop in childhood as the motor system itself develops, and are normally acquired without special effort. Other motor skills, such as juggling, playing piano, or flying an airplane, although based on existing perceptual and motor skills, require special instruction to acquire and gain expertise. Expertise in typewriting belongs in the latter class. Prospective typists spend hundreds of hours in classes and practice before they are expert enough to be employed. In fact, when typewriters were first manufactured, they were operated by the hunt and peck method. It took another twenty years or more before it was generally realized that it was even possible to type using all ten fingers and without looking at the keyboard.

A typical professional typist has accumulated an incredible amount of practice. A conservative assumption would be that a typist averages 50 words per minute (wpm) for 20 hours per week. Over the course of 10 years, that would amount to 150 million keystrokes or 25 million words. In ten years, this hypothetical typist would have typed the word the 2 million times, and typed a common word like system 10,000 times. The speed of professional typists is also quite remarkable. A typing rate of 60 wpm corresponds to an average of five keystrokes per second. The fastest typists I have studied maintain an average of more than nine keystrokes per second over the period of an hour.

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Acquisition of Typewriting

In common with the other tasks described in this book, it takes people a surprisingly long time to become expert typists. The performance norms listed by West (1983, p. 346) give the following median typing speeds for students: 38 wpm for students completing the first year of high school typing, 44 wpm for students completing the second year of high school typing, and 56 wpm for students at the end of business school training. (These scores are gross words per minute, with no correction for errors.) The surprising finding is that after three years of practice, the median graduate of business school is just barely meeting minimal employment standards. Estimating 5 hours of practice per week and 40 weeks per year, in three years a student would have accumulated about 600 hours of practice on the typewriter.

It's instructive to contrast the time required to become an expert typist with the time required to learn to fly an airplane, which is generally acknowledged to be a reasonably difficult motor skill. A private pilot's license requires only 35 hours of flight time. Even combat pilots in the U. S. Air Force have only 300 to 350 hours flying time plus another 75 hours of simulator training when they report to their operational squadron (D. Lyon, personal communication, August, 1983). Of course there are probably motivational and aptitude differences between pilot trainees and typing students, but the similarity in acquisition times makes clear that learning to type at the professional level is not an easy task.

Like other motor skills, typewriting, once acquired, is remarkably resilient. In a classic series of motor learning studies, Hill (1934, 1957; Hill, Rejall, & Thorndike, 1913) recorded data from three month-long efforts to learn typewriting that were separated by lapses of 25 years. Hill found significant savings of skill at the beginning of the second and third learning efforts, despite the intervening 25 years between efforts. Salthouse (in press) studied the performance of professional typists ranging in age from 19 to 68 years. He measured performance of the typists on a battery of tasks, including a forced-choice reaction time task on the typewriter keyboard and a normal transcription typing task. Salthouse found that performance in the transcription typing task was not correlated with age, even though performance on supposedly similar motor tasks, such as tapping speed and forced-choice reaction time, showed the usual decline with age.

Comparisons of Expert and Novice Typists

How do expert typists differ from novices? I've examined this question by comparing the performance of student typists and professional typists. For most of the studies reported here, the typists were asked to transcribe normal prose texts for about an hour. They typed on an electronic keyboard with a layout and "feel" similar to the IBM Selectric keyboard (Figure 1). Keystrokes and the corresponding times were recorded by a microcomputer with a resolution of 1 msec. The typists' finger movements were recorded on videotape.

The student typists were volunteers from the first semester typing class at a local high school. They came to the laboratory once a week between the fourth and eighth weeks of class. The expert typists were professional typists recruited from the university and local businesses. Most of the experts were typical office secretaries, but a special effort was made to recruit a few very fast typists.
Figure 1. The layout of the keyboard used in these studies. This is the standard American "qwerty" keyboard and is identical to the layout of the IBM Selectric typewriter.
Faster Interstroke Intervals

The first measure of keystroke timing examined was the distribution of interstroke intervals. Figure 2 illustrates the range of distributions found among typists, showing the distribution of interstroke intervals for a student (Typist 21) at two points in time, a typical office typist (Typist 2), and an unusually fast typist (Typist 8). This figure also demonstrates the most obvious difference between novice and expert typists: experts type faster than novices. The typing speed of the students participating in this study ranged from 13 words per minute (wpm) for one student in the fourth week of class to 41 wpm for another student in the eighth week of class. (The typing speeds reported in this chapter are gross words per minute, with no correction for errors. A word was taken to be five characters, including spaces.) The typing speed of the expert typists ranged from 61 to 112 wpm. In addition to being faster, the expert typists generally had a much lower error rate than the student typists.

How does the performance of the expert typists compare in detail with the performance of the student typists? Is expert performance simply a speeded up version of student performance, or do qualitative changes in performance occur during acquisition of typing skill? As one approach to these questions, consider the simple movement required to type two letters in sequence with the same finger, such as de. The de interstroke intervals of experts were more than twice as fast as the de interstroke intervals of students. There are only three basic ways that an expert could type the e more quickly: 1) the finger movement to type the e could start earlier; 2) the finger could travel a shorter path; 3) the finger could move faster.

To investigate this issue, I have examined the videotape records of the expert and student typists when typing the digraph de. The study included eleven expert typists ranging in speed from 61 to 112 wpm, and eight student typists in the seventh week of their typing class, ranging in speed from 17 to 40 wpm. For each typist, the 10 instances of de (5 instances in the case of student typists) with interstroke intervals closest to that typist's median de interstroke interval were selected for study. For each instance, the position of the left-middle fingertip was digitized on the videotape recording and the trajectory was calculated in three dimensional space. The time of the first visible movement toward the e key was determined from a plot of the finger trajectory. Three measures were calculated for each trajectory: 1) the lag time—the time from the initial depression of the d key until the first visible movement toward the e on the top row; 2) the path length—the distance moved by the fingertip from the beginning of the movement until the e keypress; 3) the average speed of movement—the path length divided by the movement time. The results are shown in Table 1. Surprisingly, the mean path length of the students was slightly shorter than that of the experts, so the experts were not typing the e more quickly because of a shorter path. Instead, the experts started their finger movements with a shorter lag time after pressing the d (accounting for about 60 msec of the difference in interstroke intervals), and moved their fingers about twice as fast (accounting for the remaining 150 msec).

This picture develops an interesting twist when the data are examined for each group separately. An analysis of the correlations between the interstroke interval and the three measures (see Table 2) showed that the speed of finger movement was the primary determinant of the interstroke interval for the students (r = -.92). For the expert typists, however, speed was not correlated (r = .06) with the interstroke interval. Although there was considerable variation in speed among the experts (mean speeds ranged from 231 to 524 mm/sec), the typists with higher speeds also had longer path lengths, and the two factors cancelled out. Instead, the
Figure 2. The distribution of all interstroke intervals for Typist 21 after 4 weeks (13 wpm) and 8 weeks (25 wpm) of typing class, Typist 2 (66 wpm), and Typist 8 (112 wpm).
### Table 1

**Mean Characteristics of "de" Finger Movements**

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<th>Interstroke Interval (msec)</th>
<th>Lag Time (msec)</th>
<th>Path Length (mm)</th>
<th>Average Speed (mm/sec)</th>
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<td>384</td>
<td>104</td>
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<td>152</td>
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<td>Experts</td>
<td>178</td>
<td>46</td>
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Table 2

**Correlations with Interstroke Interval (Within-Group)**

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>Students</td>
<td>+.18</td>
<td>+.51</td>
<td>-.92</td>
</tr>
<tr>
<td>Experts</td>
<td>+.74</td>
<td>+.41</td>
<td>+.06</td>
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primary determinant of the interstroke intervals among experts was the lag times. The fastest experts had very short lag times between pressing the $d$ key and starting the movement toward the $e$ key.

**Differential Speedup of Digraph Classes**

The results described for the digraph $de$ are consistent with the view that expert performance is simply a speeded up version of student performance. Recall that the experts and students had similar path lengths, but the experts had shorter lag times and moved their fingers faster than the students. When other types of digraphs are examined, however, this simple picture of expert performance is no longer adequate. Although experts typed all sequences faster than students, the increase in speed was not equal for all interstroke intervals.

For this analysis, it is useful to divide the digraphs into classes according to the fingers used to type them (the keyboard is shown in Figure 1). Repeated letters, such as $dd$ are called doubles. The remaining (non-double) digraphs typed by one finger, such as $de$, are called one-finger digraphs. Digraphs typed by two fingers on the same hand, such as $dr$, are called two-finger digraphs. And finally, digraphs typed by fingers on opposite hands, such as $do$, are called two-hand digraphs.

Figure 3 shows the median interstroke intervals for the various digraph classes as a function of the typist's overall speed. Doubles were the fastest digraph class typed by students, but were among the slowest digraphs typed by experts. The other digraph classes were all typed at about the same speed by the slowest students, but were typed at significantly different speeds by experts. One-finger digraphs were typed the slowest by expert typists, and two-hand digraphs were typed the fastest. As overall typing speed increases, the median interstroke intervals get shorter for all digraph classes, but the amount of reduction in the interstroke interval varies, depending on the digraph class. Across this group of typists, the interstroke intervals for doubles decreased by a factor of 3 from the slowest to the fastest typists. By contrast, the interstroke intervals of 2-hand digraphs decreased by a factor of 12. The interstroke intervals of 1-finger and 2-finger digraphs showed intermediate improvement, decreasing by factors of 6 and 10, respectively.

Consideration of the finger movements required to type these digraphs suggests a mechanism for the differential improvement in interstroke intervals. With two-hand digraphs, which showed the greatest improvement, it would be possible to overlap finger movements, so that the finger movement for the second letter could be started before the first letter was typed. Alternatively, at least the movement to type the first letter with one hand should not interfere with the movement to type the second letter with the other hand. In contrast, doubles and one-finger digraphs, which showed the least speed improvement, are typed by a single finger and thus no overlapped movements are possible.

The possibility of overlapped movements for two-finger and two-hand digraphs was confirmed by analysis of videotape and high-speed film records of typists' finger movements (Gentner, Grudin, & Conway, 1980; Gentner, 1981). Numerous instances were found in the videotapes of expert typists when two, or occasionally three, keystrokes were in progress at one time. The overlapping of finger movements in time is not the only way a typist can take advantage of the ability to move fingers independently. When successive letters are typed on different rows of the keyboard, moving the whole hand to type the first letter can carry the
Approximate Words per Minute

Figure 3. The median interstroke interval for double, one-finger, two-finger, and two-hand digraphs plotted as a function of the typists' overall median interstroke interval. The fastest typist (112 wpm) is on the left; the slowest typist (13 wpm) is on the right. The data on the left are from 10 skilled typists; the data at center and right are from 37 sessions with 8 student typists in the fourth through eighth week of a beginning typing class. The typists were copying normal prose. The data plotted are based on approximately 12,000 keystrokes per typist for the skilled typists, and from 3,000 to 6,000 keystrokes per typist for the student typists. Note that one-finger doubles were among the slowest for skilled typists but fastest for the students.
other finger out of position for the second letter. There were many cases on the videotape records where no overlapped movement was seen, but digraphs typed by different fingers on the same hand were faster because the second finger was not pulled out of position by the keystroke of the first finger (Gentner, 1963).

**Increase in Overlapped Movements**

The extent of overlapped finger movements varied considerably from one expert typist to another, and was moderately correlated with typing speed. Unfortunately, the direct determination of the extent of overlapping finger movements from the videotape records is very time consuming. I have, therefore, tried to estimate the extent of overlapped movements from the interstroke intervals. Although this is an indirect measure, it at least has the virtues of ease and objectivity. The basic assumption in this measure of the extent of overlapped finger movement, is that the interstroke interval for a normal one-finger digraph represents the time for a keystroke with no overlap. Interstroke intervals for two-finger and two-hand digraphs are normally shorter than for one-finger digraphs, and this estimate assumes that these shorter intervals are the result of overlapped movements. Thus for each typist, I calculated a "cross-hand overlap index" by taking the difference between the median interstroke intervals for one-finger digraphs and for two-hand digraphs, and dividing by the median one-finger interstroke interval. I also calculated a "within-hand overlap index" in an analogous fashion, as a measure of the amount of overlapping movement between two fingers on the same hand, by comparing the median two-finger and one-finger interstroke intervals. Figure 4 shows these cross-hand and within-hand overlap indices for a group of 21 expert typists with varying typing speeds. Although the absolute values of these overlap indices should not be taken too seriously, they appear to be a reliable measure of the relative extent of overlapped movements exhibited by different typists for cross-hand and within-hand movements. Figure 4 indicates that there was a modest increase in cross-hand overlapped movements as expert typists increased in speed from 60 to 112 wpm ($r = +.65$). The increase in within-hand overlapped movements with typing speed ($r = +.82$) was much greater, however, and appears to be a major contributor to the high speed of the fastest experts. Within-hand overlapped movements are negligible for the typists in the range of 60 wpm, but the fastest typists show as much overlapped movement within-hand as cross-hand. This trend is also evident on close examination of Figure 3: the fastest typists have almost identical interstroke intervals for two-finger and two-hand digraphs.

The large differences in within-hand overlap among expert typists is related to another finding. The median interstroke intervals for two-finger digraphs were more variable among expert typists than any other digraph class. This variability was based on differences in the degree to which the fingers within a hand were moved independently. Analysis of the videotape records showed that typists with rapid interstroke intervals for two-finger digraphs moved their fingers independently or actually overlapped finger movements within a hand. Typists who had slow interstroke intervals for two-finger digraphs tended to move all the fingers on a hand together and thus their other finger was often out of position to easily type the second letter of a two-finger digraph (Gentner, 1981).

**Simulation of Acquisition**

This view, that the differential speedup of digraph types is based on the possibility of overlapped movements, is supported by results from the computer simulation of a typist developed by Rumelhart and Norman (1982). Their typing simulation model is based on a
Figure 4. Cross-hand and within-hand overlap indices for expert typists, as a function of typing speed. The overlap index, plotted on the vertical axis, is a rough estimate of the fraction of a keystroke that overlaps the previous keystroke. Although the amount of cross-hand overlap increases with increasing speed, the increase in within-hand overlap is much greater.
parallel, distributed view of cognitive processes, and does not have any central planning or timing control. Instead, their simulation attempts to type several characters at once, and the interstroke intervals are a result of competition and collaboration among concurrent goals to move the fingers to the different keyboard locations.

Producing a sequence of events in the proper serial order has always been a problem for theories of action (Lashley, 1951). In the Rumelhart and Norman simulation model, the proper serial order is obtained by having each letter inhibit all following letters. Thus, the first letter in a sequence, because it is not inhibited by any other letters will normally be the most highly activated letter and will be typed first. The second letter will be inhibited by only a letter to the left and will normally have the next highest activation. The third letter will be inhibited by two letters to the left and will normally have the next highest activation, etc.

D. Rumelhart (personal communication, 1982) found that if the amount by which a given letter inhibited the following letters was varied, the simulation model showed a pattern of changes similar to the pattern of changes found in going from student to expert typists (see Figure 5). Decreasing the amount of inhibition between successive letters in the model has the effect of increasing the degree to which several letters tend to be typed at once. When the simulation model had a high level of inhibition between successive letters, and thus tended to type one letter at a time, the pattern of interstroke intervals was similar to the pattern observed with student typists. Whereas when the level of inhibition between successive letters was low, causing the simulation model to attempt to type several letters simultaneously, the pattern of interstroke intervals was similar to the pattern observed with expert typists. Thus, this simulation result suggests that an important component of the acquisition of typewriting skill is the change toward a less sequential and more overlapped mode of performance.

Overlapped Processing

The observation, that finger movements of expert typists overlap in time, suggests that the mental processes underlying the typing of successive letters also overlap in time. Figure 6 is a very schematic representation of the mental processes involved in typing three letters. It proposes that several letters are in different stages of parallel mental processing at any one time. While the finger movement is in progress for one letter, the movement is being planned for another letter, and still other letters are being read from the original text. No doubt this view of typing is much too simple-minded. For example, letters are presumably perceived as a part of words, and not as completely independent letters, as Figure 6 would suggest. The point of this figure is just to propose that the mental processing relevant to successive letters is carried out in parallel and overlaps in time. This picture of overlapped mental processing in transcription typing is supported and elaborated by a number of other studies.

A simpler model of typing would be that each letter is perceived and typed before starting mental processing for the next letter. In this model, typing is like a series of choice reaction time tasks. But a typical reaction time to perceive and type a letter is between 500 and 600 msec (Salthouse, in press). This reaction time is in reasonable accord with the interstroke intervals of beginning student typists, but the interstroke intervals of expert typists were in the range of 100 to 200 msec, much too fast for this completely sequential model. Therefore, in order to explain the short interstroke intervals of expert typists, we must postulate that the mental processing and execution of successive keystrokes overlaps in time.
Figure 5. The effect of changing the amount of inhibition between successive letters in the Rumelhart and Norman (1982) simulation model of a typist. Points on the right have the most inhibition; points on the left have the least inhibition. Decreasing the amount of inhibition decreases the average interstroke intervals and also changes the pattern interstroke intervals for the different digraph classes. Compare this figure with Figure 3.
Figure 6. A schematic representation of the mental processes involved in typing three successive letters. The mental processes, and sometimes the finger movements, overlap in time.
Another line of support for the overlapped processing model comes from experiments that vary the amount of preview that typists are allowed. For example, Shaffer (1973) presented text to an expert typist on a CRT screen, and varied the number of characters the typist could see ahead of the character being typed. When the typist could see only two characters (the character being typed and the next character) her typing speed was reduced to one-fourth her normal rate. Shaffer found that the typist had to have eight characters of preview in order to attain her normal, unlimited-preview typing rate. Saltzhouse (in press) has reported similar studies of transcription typing with variable preview, and found that a preview of about 7 characters was required for typists to attain their normal typing rate.

A closely related line of evidence supporting the overlapped processing model of typing comes from studies of eye movements. James Hollan and I recorded eye fixations during transcription typing. We found that typists were typically reading about five characters ahead of where they were typing. Butsch (1932) reported similar results in an early study of eye movements during typing. Butsch studied 19 typists and found that the faster typists tended to look further ahead in the text. The two factors compensated, so that typists of all speeds were fixating characters about one second before the character was typed.

One might ask whether, in reading ahead, typists are utilizing the larger structure of English prose to speed up their processing and performance. Several experimenters (Fendrick, 1937; Shaffer, 1973; West & Sabban, 1982) have varied the regularity in text to determine if typists are sensitive to structures larger than letters. These studies found that typing speed increases with structure up to the word level. That is, good pseudo-words were typed faster than random letters and words were typed faster still, but prose is not typed faster than random words. In a study of short range structure in the text, Grudin and Larochelle (1982) have found small effects of digraph frequency on typing speed: high frequency digraphs are typed slightly faster than matched low frequency digraphs.

I have found similar effects of word frequency. I had experts type a text containing pairs of words that differed in frequency, but shared identical four-letter sequences. For example, one pair of words was system and oyster, which share the sequence yste. On average, the inter-stroke interval in the middle of the shared sequence was typed about 10 msec faster when it was embedded in the high frequency word than when it was embedded in the low frequency word. The common thread running through the results from all these studies is that typing performance is sensitive to higher level units in the text, such as digraph and word frequency. It should be kept in mind that these higher level effects are small compared with the predominant effects of the letter sequence, as reflected in the keyboard layout and hand constraints. Nonetheless, these studies clearly demonstrate that expert typing is not merely a sequential, letter by letter process.

Cognitive Resources Available

Expert typists appear to normally have substantial amounts of unused cognitive resources. There are numerous stories of typists who can hold conversations or answer telephones while typing. Typists commonly check the original text for grammatical or spelling errors while typing. Other typists report that they usually daydream while typing or read the manuscript for content, and have little conscious awareness of typing. In addition to these anecdotes, there is some experimental data relevant to the issue of available cognitive resources.
Transcription typing involves perception (reading the original text), mental processing (translating the letters into the corresponding finger movements and planning the movements), and action (performing the keystrokes). In the experiment to be described, I looked at how increasing the difficulty of the perceptual part of the task affected overall performance. If typists normally have extra cognitive resources available, they might be able to utilize those resources to cope with the increased perceptual difficulty, with little effect on overall task performance. On the other hand, if typists do not have extra cognitive resources available, increasing the perceptual part of the task should degrade overall performance. In this experiment, I had expert typists transcribe prose from original texts that were obscured by dot screens of varying density. To determine if the dot screens in fact increased the perceptual difficulty, there was also a second task, in which the typists read aloud from the obscured texts. The results are shown in Figure 7. Performance on the reading-aloud task indicated that the obscured texts were more difficult to read; the speaking rate decreased by a factor of more than two for the highest dot density. However, the typing rate was not significantly affected by the obscuring dot screens. Apparently, the typists had excess cognitive resources available to read the obscured texts, without affecting their typing performance.

Larochelle (1983) studied the performance of novice and expert typists in a discontinuous typing task similar to the task used by Sternberg, Monsell, Knoll, and Wright (1978). In this task, typists were presented short letter strings, which might be either words, pseudo-words containing similar English digraphs, or nonwords containing few common English digraphs. After warning and start signals, they typed the letters as rapidly as possible. Larochelle measured the latency between the starting signal and the first keystroke, and the interstroke interval between successive keystrokes. The results are shown in Figure 8. Novice performance, particularly the latency until first keystroke, was degraded with pseudo-words and nonwords. If expert typing is based on higher level units such as letter sequences or words, we would expect the effect of the type of letter string would be even greater on expert performance. Instead, expert performance on pseudo-words was identical to performance on words, and nonwords were only slightly slower. This result suggests that word-level units are not a major factor in expert typing; instead, the automated performance of experts frees cognitive resources for the extra memory and planning required to type pseudo-words and nonwords.

**Performance Variability**

Finally, I briefly discuss the variability of novice and expert performance. Quantitative measures of the nature and sources of performance variability can illuminate the mechanisms that determine motor skills. Performance variability can be decomposed into two components. First, task-based variability: the variability resulting from the performance of differing tasks (for example, the difference in interstroke intervals for the digraphs ed and ec). Second, repetition variability: the variability found when the task is maintained constant. This decomposition is illustrated in Figure 9. The distribution of all interstroke intervals for a given typist is composed of a set of much narrower distributions, one for each digraph in a given letter context. I have shown (Gentner, 1982) that the main determinants of the interstroke interval are the four characters surrounding the interval. Therefore, the widths of the narrower distributions in Figure 9 represent examples of repetition variability, whereas the distance between the centers of the two distributions represents an example of task-based variability.
Figure 7. Speaking-aloud rate and typing rate by expert typists from a series of texts obscured by dot screens of varying densities. Although the speaking-aloud rates indicate that the obscured texts were more difficult to read, the typing rates were unaffected. These data are the means of three typists.
Figure 8. Performance of expert and novice typists on a discontinuous typing task. The data plotted are the latency from the start signal to the first keystroke, and the mean interstroke interval between successive keystrokes. Example letter strings are shown in parentheses. Note. From Larochelle, S. (1983), A comparison of skilled and novice performance in discontinuous typing, in W. E. Cooper (Ed.), Cognitive aspects of skilled typing (pp. 71 and 75), New York: Springer-Verlag. Copyright 1983 by Springer-Verlag. Adapted by permission.
Figure 9. The distribution of all interstroke intervals is composed of many narrower distributions of interstroke intervals in specific contexts. This is illustrated with data from Typist 4, showing the distribution of all interstroke intervals, the distribution of *io* intervals in the sequence *alor*, and the distribution of *io* intervals in the sequence *tion*. For Typist 4, the half-width of the overall distribution was 51 msec, whereas the median half-width of distributions of intervals in a fixed four-character sequence was 19 msec.
Because the interstroke interval distributions are highly skewed, I have used two non-parametric measures of variability. The absolute variability of a distribution is measured by its half-width – the difference between the third and first quartiles. The relative variability of a distribution is the half-width divided by the median. Not surprisingly, both the absolute task-based variability and the absolute repetition variability decrease dramatically with greater expertise, as the interstroke intervals decrease by an order of magnitude.

The relative variability is a more meaningful measure when performance differs by such large factors. The relative task-based variability is roughly indicated in Figure 3. The points falling on a vertical line in Figure 3 represent the median interstroke intervals of a given typist for the different digraph classes. Because the median interstroke intervals for the different digraph classes are plotted on a log scale, the vertical scatter of the medians for each typist is a measure of the relative task-based variability. If doubles are ignored for the moment, Figure 3 shows that beginning students typed the remaining three digraph classes at roughly the same speed, showing very little task-based variability. The relative task-based variability increased with skill, with the fastest experts showing the greatest variability for the three digraph classes. Inclusion of doubles complicates the picture, because beginners type doubles twice as fast as other digraphs, whereas doubles fall between 1-finger and 2-finger digraphs for the experts. Considering all four digraph classes, then, there is no major change in task-based variability with skill, although typists at the lowest and highest skill levels have greater relative task-based variability than typists of intermediate skill.

In contrast with task-based variability, students and experts showed clear differences in repetition variability. Table 3 lists the mean value of the relative repetition variability for student and expert typists. Because an interstroke interval is affected by the surrounding four-character context, repetition variability is best measured by the variability of the middle interstroke interval in a four-letter sequence. Unfortunately, many of the students did not produce enough repetitions of four-letter sequences for this type of analysis. Instead, Table 3 lists the relative variability of the second interstroke interval in a three-letter sequence (for example, the os interstroke interval in mos), which should be almost as good a measure of repetition variability. The relative repetition variability is lower for expert typists than for students. The largest difference was for one-finger digraphs, where the relative variability of experts was only a third that of students. One-finger digraphs had the highest relative variability for students, but were very regular and similar to doubles for the expert typists.

In summary, both the absolute and relative variability of expert performance is lower, compared with the variability of student performance. The difference between the relative repetition variability of expert and student typists, however, depends on the task. For example, the relative repetition variability of one-finger digraphs is dramatically lower for experts than students, but the relative variability of two-finger and two-hand interstroke intervals is only moderately lower for experts.

**Characteristics of Expert Performance**

**Cognitive versus Motoric Constraints**

When the performance of student typists is compared with the performance of expert typists, by far the largest change we see is that experts are much faster than students. Interstroke intervals decrease by factors of three to ten. This increase in speed is accompanied by a
Table 3

Mean Relative Repetition Variability for the
Second Interstroke Interval in a Three-Letter Sequence

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<tr>
<th>Digraph Type</th>
<th>Student</th>
<th>Expert</th>
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<tr>
<td>Double</td>
<td>.256</td>
<td>.149</td>
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<tr>
<td>1-finger</td>
<td>.450</td>
<td>.154</td>
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<tr>
<td>2-finger</td>
<td>.329</td>
<td>.255</td>
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<tr>
<td>2-hand</td>
<td>.382</td>
<td>.324</td>
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shift in the underlying determinants of performance. The performance of the student typists is limited primarily by cognitive constraints, whereas the performance of the expert typists is limited primarily by motoric constraints. Students type all digraph classes at approximately the same speed, regardless of the letter locations on the keyboard. The only exception is doubles, which are typed twice as fast, either because they are typed as a single unit or because movement planning is simplified for the second letter of a double. For experts, however, interstroke intervals can vary by factors of two or more depending on the keyboard location of the letters and the fingers used to type them. In general, digraphs that allow independent or overlapping finger movements are typed much faster by experts than digraphs that do not. All expert typists appear to take at least some advantage of these possibilities when typing sequences on opposite hands. The fastest typists are also able to move fingers on the same hand independently, and thus can rapidly type letter sequences involving different fingers on the same hand. Doubles and one-finger digraphs, where no overlapped movements are possible, are typed most slowly by all expert typists.

The differences in repetition variability mirror the differences in the interstroke intervals. Absolute and relative variability decrease with increasing skill. Among student typists, the relative variability of one-finger digraphs is similar to two-finger and two-hand digraphs. Among experts, however, performance on doubles and one-finger digraphs is limited by motoric constraints. Experts, therefore, type doubles and one-finger digraphs more slowly and with lower-relative variability than the other digraph classes.

Although motoric constraints are the main determinants of expert performance, small effects of cognitive constraints can be found. For example, experts type high frequency digraphs and words slightly faster than matched low frequency digraphs and words.

Adaptable, Context-Sensitive Performance

When we first started to study typists, we expected that such an over-practiced motor skill would be performed in a rigid fashion. Instead, typing has turned out to be a very flexible skill that responds easily to the varied demands of the task. Although expert typists practice primarily with prose texts, they are able to adapt their skill to novel tasks with little or no decrement in performance. For example, typists can transcribe random words or obscured texts at the same speed as normal prose. In another experiment, I asked expert typists (who did not know Dutch) to transcribe magazine articles written in Dutch. Surprisingly, they were able to do this task at a rate only about 20% lower than their normal typing rates. We have also seen that expert performance is routinely sensitive to opportunities and limitations of the task. For example, interstroke intervals are shorter for sequences which allow movement overlap, and when typists increase their overall rate, the sequences permitting overlapped movements speed up the most.

Overlapped Processing

Expert typists achieve their high speeds by overlapped, parallel processing of successive letters. This overlap is evident throughout the perceptual, planning, and often the execution phases of performance. The evidence that mental processing of successive letters overlaps in time comes from a number of studies showing that 1) there is insufficient time for serial processing of the letters, 2) the eye fixations of typists are about one second ahead of their typing, and 3) typists are responsive to text structure above the letter level.
The Expert-Novice Continuum

Expertise in typing, ranging from student typist to normal office typist to champion typist, does not lie along a single continuum. Even in the simple case of the finger movement from *d* to *e*, student progress is marked primarily by increasing speed of finger movement, whereas experts differ primarily on the amount of lag time between the first keystroke and the initiation of movement to the second key. As another example, the overlap of finger movements on opposite hands is acquired first, but the fastest typists achieve their speed by also overlapping finger movements within a hand.

Large Individual Differences

Finally, one major characteristic of expert performance in typing that has not been discussed here is individual differences. In most experimental psychology studies, it is not possible to tell whether the differences observed among subjects are significant or merely the result of random variation. The situation is different with studies of typing, however, because it is easy to record more than ten thousand keystrokes in the course of an hour, and thus obtain very high reliability for an individual subject.

Although there are many results, such as those reported in this paper, that hold for typists in general, I often find large individual differences among expert typists. Differences in typing speed among professional typists are well known. I have also found large differences in the finger trajectories for a given keystroke. Typists differ in their sensitivity to the effects of word frequency and digraph frequency. They also exhibit major differences in error rates, the pattern of errors made, and the error mechanisms. It's clear that there are many ways to be an expert typist.
References


CHIP Technical Report List


60. George Mandler. Some attempts to study the rotation and reversal of integrated motor patterns. May 1976.


82. Laboratory of Comparative Human Cognition. *Toward a unified approach to problems of culture and cognition.* May 1979.


Cognitive Science ONR Technical Report List

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