Queuing Network Modeling of Transcription Typing

CHANGXU WU and YILI LIU
University of Michigan

Transcription typing is one of the basic and common activities in human-machine interaction and 34 transcription typing phenomena have been discovered involving many aspects of human performance including interkey time, typing units and spans, typing errors, concurrent task performance, eye movements, and skill effects. Based on the queuing network theory of human performance [Liu 1996; 1997] and current discoveries in cognitive and neural science, this article extends and applies the Queuing Network-Model Human Processor (QN-MHP [Liu et al. 2006]) to model 32 transcription typing phenomena. The queuing network model of transcription typing offers new insights into the mechanisms of cognition and human-computer interaction. Its value in proactive ergonomics design of user interfaces is illustrated and discussed.

Categories and Subject Descriptors: H.1.2 [**Models and Principles**]: User/Machine Systems—*Human information processing*; I.6.5 [**Simulation and Modeling**]: Model Development; I.2.0 [**Artificial Intelligence**]: General—*Cognitive simulation*; H.5.2 [**Information Interfaces and Presentation**]: User Interfaces—*Theory and methods, Input devices and strategies, Ergonomics*

General Terms: Human Factors, Theory, Design

Additional Key Words and Phrases: Queuing network, human performance, cognitive modeling, typing

ACM Reference Format:
Wu, C. and Liu, Y. 2008. Queuing network modeling of transcription typing. ACM Trans. Comput.-Hum. Interact. 15, 1, Article 6 (May 2008), 45 pages. DOI = 10.1145/1352782.1352788. http://doi.acm.org/10.1145/1352782.1352788.

This research was supported by National Science Foundation under Grant NSF 0308000.
Authors' addresses: C. Wu, Department of Industrial and System Engineering, State University of New York at Buffalo, 414 Bell Hall, State University of New York at Buffalo, NY 14260-2050; email: changxu@buffalo.edu; Y. Liu, Department of Industrial and Operations Engineering, University of Michigan, 1205 Beal Avenue, Ann Arbor, MI 48109; email: yililiu@umich.edu.

1. INTRODUCTION

Despite the increasing popularity of speech recognition and handwriting systems [Wu et al. 2003], typing is still one of the common activities in human-computer interaction [John and Newell 1989]. In general, transcription typing is a manual activity in which a person types characters using a text input device (e.g., a keyboard) based on the textual information they perceive from a display or other sources. For example, people sometimes need to transcribe a manually written document into a computer using a standard keyboard; pilots need to manually input some textual flight control information into the aircraft system based on voice messages from the air traffic controller; police officers often need to input the plate number of a skeptical vehicle via a regular keyboard while they are driving; and cashiers have to type a UPC bar code of a product into a system using a keypad if the bar code cannot be read automatically by a scanner.

Transcription typing involves intricate and complex interactions of concurrent perceptual, cognitive, and motoric processes [Salthouse 1986a]. Numerous studies in psychology [Salthouse 1983; 1984a; 1984b; 1985; 1986a; 1986b; Salthouse and Saults 1987], human-computer interaction [Card et al. 1983; Duric et al. 2002; Fish et al. 1997; John and Newell 1989; Pearson and van Schaik 2003], and neural science [Gordon et al. 1998] have been conducted to quantify transcription typing behavior and explore its underlying mechanisms. Several decades of research have identified numerous robust transcription typing phenomena including concurrent tasks, typing errors, visuomotor coordination, and skill acquisition. Salthouse [1986a] reviewed a majority of the experimental studies and summarized the findings as a list of 29 transcription typing phenomena (referred to as the Salthouse phenomena in this article). The availability of a wide range of experimental data and an extensive list of phenomena makes transcription typing one of the best candidate tasks to test theories and models of human performance. Modeling this rich and coherent set of behavior data and phenomena with the same set of assumptions and mechanisms is an important challenge to any theory or model of human performance. In practice, many human-computer interaction tasks involve the interaction of the perceptual, cognitive, and motoric processes. Once a model can generate the interaction of these three processes and account for a wide range of phenomena in transcription typing, it can serve as a step towards modeling other tasks in human-computer interaction.

Inspired by Allen Newell's dream of unified theories of cognition (UTC) [Newell 1973], researchers have developed several important UTCs or harbingers to UTCs, including the Model Human Processor (MHP) and the GOMS family of models [Card et al. 1983; John and Kieras 1996a; 1996b; Olson and Olson 1990], ACT-R [Anderson and Lebiere 1998], SOAR [Newell 1990; Laird et al. 1987], CAPS [Just and Carpenter 1992], and EPIC [Meyer and Kieras 1997a; 1997b]. Newell [1990] regarded transcription typing as one of the major tasks to be modeled by cognitive architectures. Although these architectures have been successfully applied to modeling a variety of tasks, it seems that the only model that covers a subset of the 34 transcription typing phenomena is

TYPIST (an acronym for TheorY of Performance In Skilled Typing) developed by John [1988; 1996] (see Section 1.2 for its description).

In this article, we describe the application of a queuing network-based theory of cognition [Liu 1996; 1997; Liu et al. 2006] in modeling transcription typing. Our model not only successfully accounts for a wide range of transcription typing phenomena, but can be used to simulate and analyze typing behavior and interfaces.

This article is organized as follows. In the remaining part of this section, we first summarize the rich list of phenomena in transcription typing, followed by a summary of existing models. In the second section, we describe the queuing network model in general and its application in typing modeling in particular. In the third section, we describe the mechanisms and results of simulating transcription typing with the queuing network model. In the fourth section, we illustrate some of the potential applications of the model in HCI interface design, and the implications of the research are further discussed in the final section.

1.1 Phenomena in Transcription Typing

After Salthouse's [1986a] review of the 29 behavioral phenomena in transcription typing, additional phenomena have been identified and summarized. John [1988] summarized 2 behavioral phenomena discovered by other researchers [Gentner 1983; John 1988; Salthouse and Saults 1987]. In addition, three eye-movement phenomena and one neural imaging pattern in transcription typing have been discovered [Inhoff et al. 1992c; Rayner 1998]. These 34 phenomena are introduced in Table I as six categories [Salthouse 1986a] including basic phenomena, units of typing, typing error, skill effects, and eye-movement phenomena.

1.1.1 *Basic Phenomena.* The following 12 behavioral phenomena are categorized as the basic phenomena in transcription typing by Salthouse [1986a] and they are related to the major factors affecting the interkey time, comparison of transcription typing with other tasks, and concurrent tasks in typing. Interkey time refers to the interval between two adjacent keystrokes, and is regarded as the basic measurement of human performance in transcription typing.

—Phenomenon 1. Typing is faster than choice reaction time. Salthouse [1984a] reported that the median interkey time for skilled typists was 177ms, while the typical reaction time for a two-choice reaction time task is about 300-400ms. Based on Hick's law on choice reaction time, a typical binary choice reaction time is $150+170\times\log_2(2)$=320ms [Schmidt 1988].

—Phenomenon 2. Typing is slower than reading. Salthouse [1984a] found that the reading speed of the typists in his experiments was 253 words-per-minute (wpm), but their typing speed was only 58 words-per-minute.

—Phenomenon 3. Typing skill and comprehension are independent. Involvement of comprehension is optional while typing [Salthouse 1986a].

Table I. Phenomena in Transcription Typing

Category	**Phenomena**	**Category**	**Phenomena**
1) Basic	1. Typing is faster than choice reaction time 2. Typing is slower than reading 3. Typing skill and comprehension are independent [2] 4. Typing rate is independent of word order [1] 5. Typing speed is slower with random character order 6. Rate of typing is severely impaired by restricted preview window 7. Alternate-hand keystroke are faster than the same-hand keystroke [2] 8. More frequent character pairs are typed more quickly [1] 9. Interkey time is independent of word length 10. The first keystroke in a word is slower than subsequent keystrokes 12. A concurrent task does not affect typing	3) Errors	18. 40%-70% of typing errors are detected without reference to the typed text 19. Many substitution errors involve adjacent keys 20. Intrusion error mostly short interkey time 21. Omission error mostly long interkey time 22. Transposition error mostly occur cross-hand
		4) Skill Effects	23. Two-finger digram improves faster than one-finger digram [2] 24. Repetitive tapping rate increases with skill [1] 25. Variability decrease with skill 26. Eye-hand span increases with skill 27. Replacement span increases with skill 28. Copy span is depend on skill 29. Stopping span increases with skill 31. Learning curve follows power law of practice [1, 2]
2) Units of Typing	13. Copy span is 7-40 characters 14. Stopping span is one or two characters 15. Eye-hand span is 3-8 characters 16. Eye-hand is smaller for meaningless material than for then normal text 17. Replacement span is about 3 characters 30. Detection span is about 8 characters [1]	5) Eye Movements	[1]32. Gaze duration per character decreased with enlarging of preview window size [1] [1]33. Mean saccade size is about 4 characters [1] [1]34. Fixation duration is around 400 ms [1]

[1] Phenomenon beyond Salthouse's review [1986a].
[2] Qualitative phenomena: existing experimental studies only reported the significance levels of comparisons between different conditions rather than detailed values of dependent variables.

Nonsignificant correlations were reported between net typing speed and comprehension scores obtained in typing [Salthouse 1984a].

—Phenomenon 4. The rate of typing is nearly the same for random words as it is for meaningful text.

—Phenomenon 5. The rate of typing is slowed as the material approaches random. The difference between phenomena 4 and 5 is that the former refers the order of the words being randomized, while the latter refers to the order of characters within each word being randomized. It was found that the average interkey time in typing increased to 454ms when subjects are typing materials composed of words with random characters [Hershman and Hillix 1965].

—Phenomenon 6. The rate of typing is severely impaired by a restricted preview of the material to be typed. Decreasing the number of characters to be typed in the restricted preview increased the interkey time and severely impaired the typing rate.

—Phenomenon 7. Alternate-hand keystrokes are faster than the same-hand keystrokes (called the alternate-hand advantage). Successive keystrokes from fingers on alternate hands are 30-60ms faster than successive keystrokes from fingers on the same hand.

—Phenomenon 8. Digram (letter pairs) that occur more frequently in normal language are typed faster than less frequent digram (called the digram frequency effect). The significant difference in typing speed between the low-frequency digrams and the high-frequency digrams has been reported in numerous studies [Salthouse 1984a; 1984b].

—Phenomenon 9. Interkey time is independent of word length. Salthouse [1986a] summarized several experiments in transcription typing and found no significant difference between the interkey time in typing long words and short words.

—Phenomenon 10. The first keystroke in a word is slower than the subsequent keystrokes (called the word initiation effect). Salthouse [1986a] reviewed 5 researchers' experiments and found that the interval before the first keystroke in a word is approximately 20% (45ms) [Salthouse 1984a] longer than that between the later keystrokes in the word.

—Phenomenon 11. The time for a keystroke is dependent on the specific context in which the character appears, especially for the topography of the keyboard (called the context phenomenon). The specific context here refers to the character ahead of and behind the target character. The context phenomenon is a combination of the alternate-hand advantage (phenomenon 7), the digram-frequency effect (phenomenon 8), the word-initiation effect (phenomenon 10), and, more specifically, the effect of topography of the keyboard in interacting with prior and subsequent keystrokes. For example, in typing the key sequence "r-e", the close proximity of the two keys "r" and "e" in the same row on a standard QWERTY keyboard allows the middle finger on the left hand to move toward the target "e" while the index finger on the left hand is typing character "r", which may save half of the movement distance of the middle finger from the home position “d” to the target position “e”.

—Phenomenon 12. A concurrent task does not affect typing performance. For highly skilled typists, a concurrent activity can be performed with little or no effect on the speed or accuracy of typing. Salthouse and Saults [1987] added a secondary task in parallel with the primary task of transcription typing: typists were asked to press a foot pedal as soon as they heard a tone signal [Salthouse and Saults 1987]. They found that the interkey time in this concurrent task situation was 185ms, which was not significantly longer than that in a single task situation (transcription typing only, interkey time 181ms).

1.1.2 *Units of Typing.* This group contains six phenomena related to the various spans and units of typing (defined later), five of which appeared on the original list of Salthouse [1986a] and the last one was identified after the list was published [Salthouse and Saults 1987]. It was regarded as one of the post 29 phenomena (phenomenon 30) by John [1996].

—Phenomenon 13. Copying span is 2-8 words or 7-40 characters for all typists. *Copying span* is the amount of characters that can be typed accurately after a single inspection of the copy [Salthouse 1986a]. Without requiring the typists to commit the material to be typed to memory before typing or by randomizing the order of the words, Salthouse [1985] measured the copying span as the number of characters typed correctly after an unexpected disappearance of the copy and found that the copying span in normal transcription typing situation was 14.6 characters on average for the skilled typist.

—Phenomenon 14. Stopping span is one or two characters. *Stopping span* is the number of keystrokes typed after the subjects were requested to terminate their typing immediately after perceiving a stop signal. Using an auditory stop typing signal, Logan [1982] found that the stopping span was 2.16 characters when the typing materials were sentences.

—Phenomenon 15. Eye-hand span is 3-8 characters. *Eye-hand span* is defined as the number of characters intervening between the character whose key is currently being pressed and the character receiving the attention of the eyes [Salthouse 1986a]. Butsch [1932] found that the eye-hand span was 5 characters. The result is consistent with the other studies reviewed by Salthouse [1986a] who found that the range of eye-hand span is between 3 to 8 characters.

—Phenomenon 16. Eye-hand span is smaller for unfamiliar or meaningless material than for normal texts. When typists were typing a text and each word in it was composed of randomly ordered letters, Salthouse [1984a] found that their eye-hand span was only 1.75 characters.

—Phenomenon 17. Replacement span is about 3 characters. The subjects in Salthouse and Saults [1987] were asked to type exactly what appeared on the screen where one of the characters to be typed could be suddenly replaced by another character. *Replacement span* is defined as the keystroke-replacement interval corresponding to a 0.5 probability of typing the second (replaced, i.e., newly appeared) character. The replacement span was 2.9 characters on average [Salthouse 1986a].

—Phenomenon 30. Detection span is about 8 characters. In the experiment of Salthouse and Saults [1987], subjects were asked to press the "/" key when they noticed a capital character on the line. The *detection span* is defined as the number of characters intervening between the capital character and the character currently being typed. The observed mean detection span was 8 characters approximately.

1.1.3 *Errors in Transcription Typing.* Salthouse [1986a] classified the vast majority of typing errors into four categories: substitution (e.g., work for word), intrusion (e.g., worrd for word), omission (e.g., wrd for word) and transposition (e.g., wrod for word). He summarized five major typing error phenomena related to these four categories of errors.

—Phenomenon 18. 40%-70% of typing errors are detected without reference to the typed text. After reviewing three studies in transcription typing, Salthouse [1986a] summarized that about 40%-70% of typing errors are detected without reference to the typed copy. In his review, Salthouse suggested that typing errors include: (a) undetected errors which can be postulated to originate at earlier levels of processing (errors mainly caused by failure to preserve sequences in the sensory and working memory) and (b) detected errors without reference to the typed copy which probably stem from later stages of processing (hand and finger movement) that are handled by the efferent response feedback.

—Phenomenon 19. Many substitution errors involve adjacent keys. Experimental results from highly skilled typists indicated that 30.1% of substitution errors involved horizontally or vertically adjacent keys [Salthouse 1986a].

—Phenomenon 20. Many intrusion errors involve extremely short interkey time in the immediate vicinity of the error. Nearly 38% of the intrusion error keystrokes had ratios (interkey time of an error keystroke divided by that of the regular interkey time) less than 0.1 of the average interkey time [Salthouse 1986a] and over 54% of intrusion errors involved an adjacent key in the same row or the same column.

—Phenomenon 21. Many omission errors are followed by a keystroke interval approximately twice the overall median. Salthouse [1986a] summarized this phenomenon based on Shaffer's study [1975] which found that the interkey time of the keystroke right after the omission error was 1.54 times longer than that of the average interkey time.

—Phenomenon 22. Transposition errors mostly occur cross-hand. Salthouse [1986a] reported that 80% of the transposition errors were typed by the opposite hands.

1.1.4 *Skill Effects in Transcription Typing.* Salthouse [1986a] summarized seven phenomena related to the improvement of typing performance through practice. In addition, Gentner [1983] found another related phenomenon—the interkey time of transcription typing decreases with practice following the power law, which is listed in the following as one of the post 29 phenomena (phenomenon 31).

—Phenomenon 23. Digrams typed with two hands (two-hand digrams) or with two different fingers of the same hand (two-finger digrams) exhibit greater changes with the skill level of typists than do digrams typed with one finger. Salthouse [1984a] found that the slope of the regression equations relating the digram interval to typing speed of two-hand digrams (-2.08) and two-finger digrams (-2.38) were greater than that of one-finger digrams (-1.38 on average).
—Phenomenon 24. Repetitive tapping rate increases with the skill level of typists. Salthouse [1984a] found a significant positive correlation between the tapping rate and the net typing speed ($p < .01$).
—Phenomenon 25. The variability of interkey time decreases with the skill level of typists. Salthouse [1984a] found that two types of variability of the interkey time (75% quartile-25% quartile) decreased with an increase in typists' skill level: (a) Inter-keystroke variability, which refers to the distribution of interkey time across different keystrokes and different contexts, correlated -.69 with the net typing speed; (b) Intra-keystroke variability, which represents the distribution of interkey time for the same keystroke in the same context but across multiple repetitions, correlated -.71 with the net typing speed.
—Phenomenon 26. Eye-hand span is larger with increased skill level of typists. In the Salthouse [1984b] studies, the correlation between the eye-hand span and net words-per-minute across 74 typists was significant with $p < .01$. There was an increase of between 0.5 and 1.2 characters with every 20 net words-per-minute increase in typing skill [Salthouse 1985; Salthouse and Saults 1987].
—Phenomenon 27. Replacement span is larger among more skilled typists. Salthouse's studies [1985] found that the correlation between net words per minute and the replacement span was 0.80 ($p < .01$).
—Phenomenon 28. Copying span is moderately related to the skill level of typists. The correlation coefficient between copying span and net words-per-minute ranges from 0.35 to 0.57 [however, the correlation is not significant, $p > .05$ Salthouse [1985].
—Phenomenon 29. Fast typists have larger stopping spans than slow typists. The experimental results of phenomenon 29 are not conclusive. Salthouse and Saults [1987] reported a correlation of 0.57 between the typing speed and the stopping span. However, another study of Salthouse [1985] did not find any significant correlation between these two variables ($p > .05$).
—Phenomenon 31. Interkey time of transcription typing decreases with practice following the power law of practice [Gentner 1983]. Typing speed of an unskilled typist can be improved to that of a skilled typist. According to the learning curve of the single typist in the study of Gentner, the improvement of interkey time follows the power law of practice.

1.1.5 *Eye-Movement Phenomena.* Although not included in the Salthouse list of phenomena, eye movements are one of the most important aspects of human behavior in eye-hand coordination tasks including transcription typing. Among the various variables in eye movements data, fixation duration (the length of time for one fixation of the eye movements), saccade size (the number of characters or the degrees of visual angle between two fixation points) and gaze duration-per-character (equals fixation duration divided by saccade size) are the major parameters in determining eye movements in transcription typing [Inhoff et al. 1992a; 1992b]. Three recently discovered eye movements phenomena related to transcription typing are listed here.

—Phenomenon 32. Gaze duration-per-character decreases with increased preview window size. Inhoff et al. [1992a; 1992b] found that the gaze duration-per-character decreased from 280ms to 182ms when the preview window size increased from 1 to 11 characters.

—Phenomenon 33. The mean saccade size is about 4 characters [Rayner 1998].

—Phenomenon 34. The mean fixation duration in transcription typing is 400ms [Rayner 1998].

1.2 Existing Models of Transcription Typing

Several quantitative and qualitative models have been proposed to analyze transcription typing behavior. The quantitative models includes a central control model [Terzuolo and Viviani 1979; 1980], a composite model [Gentner 1987], an activation-trigger-schema model (Rumelhart and Norman, 1982), and a PERT-network based model [John 1988; 1996]. The model proposed by Salthouse [1984a; 1986a] is a qualitative model.

Terzuolo and Viviani [1979; 1980] proposed a central control model of timing in transcription typing and they suggest that interkey time is generated in parallel from centrally stored, word-specific timing patterns. Gentner [1983] provided experimental evidence against this central model and proposed a composite model composed of both central and peripheral mechanisms [Gentner 1987].

Rumelhart and Norman [1982] proposed a model based on an activation-trigger-schema system in which a hierarchical structure of schemata directs the selections of the characters to be typed and controls the hand and finger movements by a cooperative algorithm. The model reproduces several major phenomena of typing including the interkey time and the patterns of transposition errors found in skilled typists.

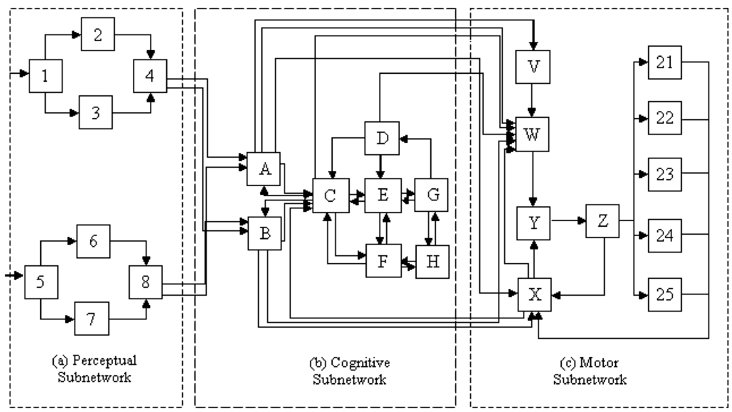
John [1988; 1996] proposed a model called TYPIST which uses the Project Evaluation and Research Technique (PERT) method of scheduling to quantify the parallel activities of typing performed by the three perceptual, cognitive, and motor processors in the Model Human Processor (MHP) [Card et al. 1983]. TYPIST is by far the most extensive quantitative model of transcription typing and it covers 19 of the 34 phenomena in transcription typing, including 17 phenomena reviewed by Salthouse [1986a; 1986b] and 2 additional phenomena found by Gentner [1983] and Salthouse and Saults [1987] (phenomena 31 and 30 reviewed earlier).

Salthouse [1984a; 1986a] proposed a qualitative model of transcription typing which consists of 4 components: input (convert text into chunks), parsing (decompose chunks into ordinal strings of characters), translation (convert characters into movement specifications) and execution (implement movement in ballistic fashion). It is a synthesis of many previous works and provides a basic conceptual framework in transcription typing. However, because it is a qualitative model, it does not simulate or generate typing behavior or make quantitative predictions.

In the following section, we describe a queuing network model of human performance and its application in modeling transcription typing. The model captures the nature of transcription typing as a parallel process. The typist looks ahead at the words on a display while executing the motor responses for the current characters [John and Newell 1989]. The model analyzes time and error simultaneously with the same underlying cognitive structure and generates typing behavior as observable behavioral manifestations of the underlying cognitive queuing network at work.

2. QUEUING NETWORK MODELING OF HUMAN PERFORMANCE

Along the line of research on developing unified theories of cognition advocated by Newell [1990], we have been making steady progress in developing a queuing network architecture for human performance modeling [Liu 1996; 1997; Liu et al. 2006]. Mathematical models based on queuing networks have successfully integrated a large number of mathematical models in response time [Liu 1996] and in multitask performance [Liu 1997] as special cases of queuing networks. As a computational model, we have established a bridge between the mathematical models of queuing networks and the symbolic models of cognition with our queuing network architecture called the Queuing Network-Model Human Processor (QN-MHP) [Liu et al. 2006]. The QN-MHP represents its overall architecture as a queuing network, a major branch of mathematics and operations research, thus allowing comprehensive mathematical modeling. Further, each of the QN-MHP servers is capable of performing procedure logic functions, allowing it to generate detailed task actions and simulate real-time behavior like symbolic models such as ACT-R and EPIC. For multitask performance modeling, a unique characteristic of the QN-MHP is its ability to model concurrent activities without the need to either interleave the production rules of concurrent tasks into a serial program (in ACT-R) [Anderson et al. 2004; Salvucci 2005] or for executive process(es) to interactively control (lock/unlock) the task processes (in EPIC). The model has been successfully applied to model a variety of tasks including simple and choice reaction time [Feyen and Liu 2001], visual search [Lim and Liu 2004], visual manual tracking [Wu and Liu 2006a], psychological refractory period (PRP) [Wu and Liu 2004], and driver workload [Wu and Liu 2006b; 2006c]. For a detailed description of the rationale, assumptions, structure, and implementation of the QN-MHP and how to use it in multitask modeling, see Liu et al. [2006].



Perceptual Subnetwork
1. Common visual processing
2. Visual recognition
3. Visual location
4. Visual recognition and location integration
5. Common auditory processing
6. Auditory recognition
7. Auditory location
8. Auditory recognition and location integration

Cognitive Subnetwork
A. Visuospatial sketchpad
B. Phonological loop
C. Central executive
D. Long-term procedural memory
E. Performance monitor
F. Complex cognitive function
G. Goal initiation
H. Long-term declarative & spatial memory

Motor Subnetwork
V. Sensorimotor integration
W. Motor program retrieval
X. Feedback information collection
Y. Motor program assembling and error detecting
Z. Sending information to body parts
21-25: Body parts: eye, mouth, left hand, right hand, foot

Fig. 1. The general structure of the queuing network model (QN-MHP 2.0). Further developed from Liu et al. [2006].

In this section, we describe four new developments of the QN-MHP that are beyond the first version (called QN-MHP 1.0, for ease of description) reported in Liu et al. [2006]: the auditory subnetwork in the perceptual subnetwork, the phonological loop and the long-term memory servers in the cognitive subnetwork, refinements of the motor network, and three learning mechanisms. These developments are important for a broader coverage of human performance since they are well-recognized components of human performance in the literature. As described in the following, these developments are developed and implemented context-free, independent of any particular task, and then applied to the modeling of the wide range of phenomena in transcription typing.

2.1 Enhancement of the Perceptual Subnetwork

The general structure of the QN-MHP is shown in Figure 1, and consists of a perceptual, a cognitive, and a motor subnetwork. The perceptual subnetwork includes a visual and an auditory subnetwork and each of them is composed of four servers. The visual subnetwork was implemented in the QN-MHP 1.0 and discussed in Liu et al. [2006]. The auditory subnetwork (server 5-8), however, was not developed in the original version; thus none of the tasks modeled with QN-MHP 1.0 included auditory information processing. Clearly, many real-world tasks involve auditory processing such as using a telephone or listening to voice instructions. Several of the transcription typing phenomena listed earlier also involve auditory information processing. To cover these types of tasks, one of the enhancements of the queuing network model is the development and implementation of the auditory subnetwork.

The auditory subnetwork is developed in the queuing network model as follows. The auditory stimuli (represented by numeric code) are converted to auditory information (represented by entities) in the middle and inner ear (represented by server 5) and then transmitted to the parallel auditory pathways including the neuron pathway from the ventral cochlear nucleus to the superior olivary complex (server 7) and the neural pathway from the dorsal and ventral cochlear nuclei to the inferior colliculus (server 6) where location pattern and other aspects of the sound are processed Bear et al. [2001]. After that, the auditory information in the auditory pathways is integrated at the primary auditory cortex and the planum temporale (server 8) [Mustovic et al. 2003]. The primary auditory cortex and the planum temporale as well as the auditor pathways (server 6-8), also serve as a sensory memory storage place for the auditory information [Mustovic et al. 2003]. Further, based on the mechanism of working memory of Baddeley [1992], the auditory information is transmitted to the left-hemisphere posterior parietal cortex (server B) as well as the right-hemisphere posterior parietal cortex (server A) through the neural pathways between the primary auditory cortex and the posterior parietal cortex as well as the angular and supramarginal gyri which are regarded as multimodal areas responding to visual, auditory, and somatosensory stimuli [Faw 2003]. Information processed in the perceptual subnetwork decays following the decay rate of sensory memory in MHP [Card et al. 1983]; the half-life of visual and auditory information is 200ms and 1500ms, respectively.

2.2 Enhancement of the Cognitive Subnetwork

2.2.1 *Phonological Loop.* The phonological loop is developed on the basis of Baddeley's model of working memory [Baddeley 1992] and related neuroscience findings. In Baddeley's model, the working memory system includes a visuospatial sketchpad, a phonological loop, and a central executor. The visuospatial sketchpad (server A) and central executive (server C) were already developed in QN-MHP 1.0. Server B is developed and implemented in QN-MHP 2.0 to represent the functions of two particular regions of the phonological loop in the brain: (1) the left-hemisphere posterior parietal cortex which stores phonological information in working memory; (2) the Broca's area (BA) 44 and 45 which are important for encoding visual information to phonological representation (e.g., forming phonological chunks as meaningful units) [Smith and Jonides 1998], articulating speech and subvocal rehearsal. The left-hemisphere posterior parietal cortex as well as BA 44 and 45 (all of them represented by server B) are densely connected with the DLPFC (dorsal lateral prefrontal cortex) and the ACC (anterior cingulate cortex) (server C) as well as the basal ganglia (server W) [Bear et al. 2001]. Information processed in server B decays following the decay rate of working memory in MHP [Card et al. 1983].

2.2.2 *The Long-Term Memory Servers.* QN-MHP 2.0 contains two types of long-term memory based on neuroscience studies (a) declarative (facts and events) and spatial memory and (b) nondeclarative memory (procedural memory and motor program) [Bear et al. 2001]. As the first step in model development, QN-MHP 1.0 includes only one type of long-term memory, which is implemented as a database as an input to the model (model retrieves certain information in this database based on different tasks) rather than an explicit server of the QN-MHP architecture. To be consistent with existing psychological findings on the structure of long-term memory and to model a wider range of behavior, QN-MHP 2.0 explicitly includes the two types of long-term memory as two servers in the cognitive subnetwork. This development is also consistent with the use of two long-term memory systems in ACT-R.

In Figure 1, server H represents long-term declarative and spatial memory and server D represents long-term nondeclarative memory (procedural memory and motor program). This development is based on the neuroscience findings that the medial temporal lobe including the hippocampus and the diencephalons (server H) is the storage place for declarative and spatial memory. The medial temporal lobe connects with the IPS (intraparietal sulcus) (included in server F) and the orbitofrontal region (server G) [Bear et al. 2001; Cook and Woollacott 1995; Kaufer and Lewis 1999]. Long-term declarative and spatial memory (sever H) stores long-term spatial information and production rules related to decision making and problem solving. The striatal and cerebellar systems (server D) are related to the procedural long-term memory which connects with ACC (server C) and basal ganglia (server W) [Bear et al. 2001]. In QN-MHP, the capacity of the two types of long-term memories is assumed to be infinite. Procedural long-term memory (server D) stores all of the steps in task procedures and motor programs related to motor execution.

2.3 Enhancement of the Motor Subnetwork

The major part of the motor subnetwork in the QN-MHP 2.0 is the same as the QN-MHP 1.0. There are several major improvements in the QN-MHP 2.0.

First, functions of server Y (representing the SMA and the pre-SMA) are enhanced since neuroscience has found the SMA not only assembles the motor programs, which is covered by QN-MHP 1.0, but also processes tactile information from the somotosensory area (S1) (server X) to detect errors [Gordon and Soechting 1995; Sadato et al. 1997] and coordinate and couple the bimanual coordination [Steyvers et al. 2003].

Second, in the QN-MHP 1.0, one server (server Z) represents all of the actuators and no server in the motor subnetwork represents the primary motor cortex. In modeling typing as well as other bimanual tasks, the primary motor cortex plays an important role in sending input information to different body parts including addressing spinal motorneourons [Bear et al. 2001]. Therefore, in QN-MHP 2.0, server Z is used to represent the primary motor cortex, while servers 21-25 represent the different body parts (e.g., eye, mouth, right and left hands and feet).

Third, hand and foot servers are newly built servers in the QN-MHP 2.0. Each of these servers can process information in a serial manner. The movement execution time and force in these servers are quantified based on previous research in human factors and ergonomics (see Appendix 3). In addition, entities in the motor subnetwork decay following the decay rate of motoric information with half-life equaling 1000ms on average [Ito 1991].

2.4 Learning Mechanisms in the Queuing Network

Another important improvement of the queuing network model is its development and implementation of three learning mechanisms, none of which were included in QN-MHP 1.0. At network level, the probability that entities take different routes may change in the learning process, representing the change of connection strengths and rewiring of neural pathways in the brain network [Van Mier et al. 1998; Petersen et al. 1998]. At the individual servers, level, server processing time decreases and information processing in servers can also be optimized via trial-and-error, reflecting the improvement of information processing efficiency of individual brain regions via a learning process [Braus 2004; Boettiger and D'Esposito 2005].

2.4.1 *Change of Routing Probability*. It is well recognized that the human brain is not only a network of brain regions, but also a system that is able to change itself dynamically in the process of development and learning [Chklovskii et al. 2004; Habib 2003]. On the one hand, the "brain traffic" concept in neuroscience suggests that information flow represented by spike trains in the brain exhibit features of traffic flow in the network; spike trains (represented by entities in the model) form the information flow among brain regions. Depending on different tasks and learning stages, these information flows can sometimes be processed immediately by the brain regions (servers), but sometimes they have to be maintained in certain regions to wait for the previous flow to be processed [Bullock 1968; Eagleman et al. 2004; Smith and Jonides 1998; Taylor et al. 2000; Braus 2004; Chklovskii et al. 2004; Habib 2003]. On the other hand, different brain areas are activated during the visual-motor learning process [Van Mier et al. 1998; Petersen et al. 1998; Aizawa et al. 1991]. This plasticity aspect of the human brain concerns the change of synaptic connection strength between neurons and rewiring among neural pathways; spike trains change from one neural pathway to anther one with stronger synaptic connection strength and higher efficiency in information processing. This rapid regulation is related to a brain derived neurotrophic factor (BDNF) regarded as a signal of synaptic plasticity in adults [Black 1999; Braus 2004], and Black [1999] proposed a model explaining the role of BDNF in its regulation of the synaptic plasticity.

Equation (1) is developed based on Black's model [1999] and the brain traffic concept mentioned previously (see Appendix 1 for its derivation), where routing probability (P_i) stands for the probability that spike trains (represented by entities) pass through a certain neural pathway (route i) in a total of U multiple routes. Sojourn time (S_i) is defined as the sum of waiting time (W_i) and processing time (T_i) of these spike trains (entities) along that neural pathway.

$$P_i = \frac{1/S_i}{\sum_{j=1}^{U} \frac{1}{S_j}} \tag{1}$$

2.4.2 *Reduction of Server Processing Time.* Besides the change of connection strengths and rewiring of pathways at the network level, individual brain regions also exhibit improvements in information processing speed in the learning process [Braus 2004]. Moreover, some research has demonstrated that exponential functions characterize the learning processes in memory search, motor learning, visual search, and mathematic operation tasks better than the power law [Heathcote et al. 2000]. Accordingly, exponential functions are employed in the queuing network model to characterize the learning process in the individual servers (see Equation (2)) with the exception of the six perceptual servers (servers 1-3 and 5-7) that are only related to neural signal transmissions which are relatively stable in the learning process.

$$T_i = A_i + B_i Exp(-\alpha_i N_i) \tag{2}$$

In Equation (2), $T_i$stands for the processing time in each server; A_i represents the expected minimal processing time (Ti) at server i after intensive practice [Feyen 2002]. B_i is the change in the expected processing time from the beginning to the end of practice; α_i represents the learning rate of server i (e.g., α_i= .001 [Heathcote et al. 2000]); and N_i is the number of entities processed by server i; for example, N_i in servers A, B, C, and F refers to the number of chunks the server processed, while N_i in server W refers to the number of retrievals of a certain motor program in general (e.g., in transcription typing, N_i in server W refers to the number of retrievals for a certain digram).

2.4.3 *Optimization of Information Processing via Trial-And-Error.* Numerous studies have found that mammals including human beings optimize their movement and behavior via the learning process [Alexander 1993; Borghese and Calvi 2003; Laureys et al. 2001]. For example, mammals optimize the movement of their legs to run quickly with the smallest amount of energy. Among these optimization processes, trial-and-error is one of the major formats of learning [Boettiger and D'Esposito 2005; Bustillos and De Oliveira 2004; Ghilardi et al. 2000; Sakai et al. 1998]. Mammals may try many actions until one of them satisfies their goal. For human beings, trial-and-error is also an important aspect of motor learning [Ghilardi et al. 2000] and optimization in information processing in working memory [Asari et al. 2005; Baltes et al. 1999; Bor et al. 2004; Genovesio et al. 2005; Krampe et al. 2003; Schmuck and WobkenBlachnik 1996], and it involves the activation of the frontal cortex (represented by server A, B, C) and the presupplementary motor area (pre-SMA, represented by server Y) [Boettiger and D'Esposito 2005; Nakamura et al. 1998]. Typically, this trial-and-error learning is simulated via Monte Carlo simulation [Bustillos and De Oliveira 2004] whose nature is a trial-and-error process of using random numbers to reach a solution. In general, this Monte Carlo learning mechanism can be implemented in any of the QN-MHP servers, but for transcription typing modeling, it is only implemented in server B and server Y since they are most relevant to learning of motor skill and keyboard characteristics.

3. SIMULATING TRANSCRIPTION TYPING WITH QN-MHP: MECHANISMS AND RESULTS

Simulation of any human-machine interaction task requires the specification of three components: a human model, the machine or the environment with which the human model interacts, and the task input to the human model. These three components correspond to the QN-MHP, a typewriter, and a display presenting the text to be typed, respectively, in the context of the transcription typing task.

The general human model of QN-MHP is described in the previous section. To possess the basic knowledge of typing requires the QN-MHP to have the corresponding procedure knowledge rules stored in its long-term procedure memory server. Thus, following the general method of QN-MHP simulation [Liu et al. 2006], a 5-step NGOMSL-style task description of transcription typing is developed (see Table II) and stored in server D as the long-term procedure knowledge of typing in the model (also called operator or command entity). Step 1 (watch for < > on < >) defines how the model samples visual information (e.g., the characters) on a certain user interface (e.g., the display) via the visual perceptual subnetwork following a queuing process. The number of entities leaving server A or B at one time, forming a chunk (a meaningful information unit, chunk size=x), determines the number of entities sampled by the servers in the visual perceptual subnetwork at one time. After the stimuli are retained in the working memory (step 2), step 3 defines how the model presses a certain control device on a user interface (e.g., keys on a QWERTY keyboard) with defined body parts (e.g., hands). Finally, when the model reaches the end of the text (step 4), it stops typing (step 5). All of these steps or operators have two properties. First, they are defined in a task-independent manner; task-specific information is treated as their parameters. Second, even though these steps are listed in a serial manner in the NGOMSL-style task description, they can run in parallel in the model because of the parallel processing property of the queuing network. For example, the perceptual subnetwork is able to watch for new stimuli (step 1), while the motor subnetwork is still executing the simulated actions (step 3).

To define a typewriter with which the QN-MHP interacts, a software module called m-hQWERTY was implemented to represent a QWERTY keyboard, the most commonly used keyboard in the English-speaking world. This module defines the size and location of each key and the distance between each pair of the keys on the keyboard. We selected the same text source employed in Salthouse's study [1984a; 1984b; 1987], the Nelson-Denny Reading Test. A module in the simulation software (Promodel®) is designed to represent the display containing the position and content of the text characters. In each run,

Table II. NGOMSL-Style Task Description of Transcription Typing Task

GOAL: Do transcription typing task
Method for GOAL: Do transcription typing task
Step 1. Watch for <the characters> on <the display>
Step 2. Retain <the characters >
Step 3. Press <keys> on <a QWERTY keyboard> with <hands>
Step 4. Decide: If <the characters> is <the end of text>, then move to step 5
Else move to step 1
Step 5. Cease //task completed
Method for GOAL: Press <keys> on <a QWERTY keyboard> with <hands>
Step 1. Decide: If location of <keys> in memory, then move to step 3
Else move to step 2
Step 2. Visual search for <locations> of <keys> on <a QWERTY keyboard>
Step 3. Reach <keys> on <a QWERTY keyboard> with <hands>
Step 4. Return with goal accomplished
Method for GOAL: Visual search for <locations> of <keys> on <a QWERTY keyboard>
Step 1. Recall <characters> from <working memory> as <the target characters>
Step 2. Watch for <key labels> on <a QWERTY keyboard>
Step 3. Compare <key labels> with <the target characters>
Step 4. Decide: If match, then move to step 5
Else move to step 2
Step 5. Retain <the location> of <key labels>
Step 6. Return with goal accomplished

the model types 1,000 letters from the Nelson-Denny Reading Test; and the model performed 10 simulation runs with different standard random number series in the Promodel software [Promodel 2004].

In the following, the simulation mechanisms and results are described in detail for each of the six groups of phenomena just reviewed. In each group, we describe how the corresponding phenomena are generated based on the mechanisms in the queuing network. Simulation results were validated with the same error estimation calculation method employed in John [1988; 1996], including the percentage of relative error = $|Y - X| / X \cdot 100\%$, Y: simulation result; X: experimental result, which is summarized at the end of this section.

3.1 Basic Phenomena

3.1.1 *Simulation Mechanisms.* The ten phenomena in this group are modeled with three fundamental mechanisms of the QN-MHP: parallel processing (phenomena 1, 7, 12), motor processing (phenomena 4, 5, 6, 8, 9, 11), and visual processing (phenomenon 10).

(1) Parallel Processing (Phenomena 1, 7, 12). Phenomena 1, 7, and 12 emerge naturally as the result of parallel processing in the queuing network. Typing is faster than choice reaction time (phenomenon 1) because the servers in the visual perceptual subnetwork of the QN-MHP can process visual entities (watch for the remaining letters to be typed) at the same time while the motor servers execute typing actions. This is in contrast to a choice reaction time task which requires a single response execution to follow stimuli perception in a

serial manner. In the QN-MHP, the two hand servers can process information in parallel, while each hand can only process information serially, producing phenomenon 7, namely alternate-hand keystrokes are faster than same-hand keystrokes. Similarly, a concurrent task does not affect typing (phenomenon 12) when it involves the servers and routes that can be performed concurrently with the typing task, as in the case of the tone-pedal pressing task (see Table III for its NGOMSL task description).

(2) Motor Processing (Phenomena 4, 5, 6, 8, 9, 11). The motor subnetwork in the queuing network model is able to generate these 6 phenomena in a natural and consistent manner. In the motor subnetwork, motor programs of high-frequency digrams are retrieved more often by server W from server D, requiring less processing time than low-frequency digrams and producing the digram frequency effect according to Equation (2) (phenomenon 8). Correspondingly, if all of the letters to be typed are composed of random ordered letter pairs, this digram frequency effect disappears and the interkey time increases (phenomenon 5). Similarly, if the model can only sample one or two characters at one time via the preview window, it increases the chance that motor programs of high-frequency digrams are decomposed and therefore attenuates this digram frequency effect, producing phenomenon 6, the typing rate is impaired by the restricted preview window. In contrast, if only the order of the word is randomized but the order of the letters in each word remains unchanged (phenomenon 4) or the number of letters in each word increases (phenomenon 9), this digram frequency effect is not affected since the digrams in each word are still preserved, generating phenomena 4 and 9, that is, interkey time is independent of word order and its length. In addition, step 3 in the NGOMSL-style task description (press < > on < > with < >), a task-independent operator treating task-specific information such as keyboard layout as its parameters, specifies how the two hand servers interact with a QWERTY keyboard (implemented in the m-h QWERTY module) and generates the movement distance of fingers according to the topography of the keyboard. Then the hand servers in the model are able to produce the movement time of fingers (see Appendix 3), producing phenomenon 11, the keystroke time depends on the specific context. It is important to note that there is no free parameter in the formula to simulate the experimental results.

(3) Visual Processing (Phenomenon 10). Phenomenon 10 is produced by the model naturally via its visual sampling process defined in the "watch for" operator. The hunt-feature production which is employed by ACT-R and implemented in QN-MHP, facilitates the servers in the visual perceptual subnetwork to locate the fixation point at the feature of a meaningful unit, the middle point of the first half of a word [Rayner 1998] in the text-viewing condition. This process indicates that the first character in each word is the expected first character in each chunk (see calculations in Appendix 2), which increases the processing time of the first character of each word by the time needed in encoding visual stimulus into chunks, producing phenomenon 10, the keystroke of the first character is longer than that of other keystrokes in a word.

Table III. NGOMSL-Style Task Description of Tone-pedal Press Task

GOAL: Do tone-pedal pressing task
Method for GOAL: Do tone-pedal pressing task
Step 1. Listen to <the tone> from <the speaker>
Step 2. Retain <the tone>
Step 3. Compare: <the tone> with <the target tone> in memory
Step 4. Decide: If match, then go to step 5
Else move to step 1
Step 5. Press <the pedal> on <the floor> with <one foot>
Step 6. Return with goal accomplished

3.1.2 *Simulation Results.* QN-MHP showed an average interkey time of 176ms, which was shorter than the choice reaction time modeled by QN-MHP 1.0 (the typical two choice reaction time is 320ms, [Feyen 2002] (phenomenon 1, estimation error= 0.56%). In these keystrokes, the simulated alternate-hand strokes were 40ms shorter than the same-hand strokes on average (phenomenon 7, estimation error= 11%). The simulated average interkey time in the concurrent task situation was 174ms which was not affected by the pedal-pressing task and no significant difference in the number of typing errors (Kolmogorov-Smirnov Test, Z=0, df=18 (10 runs for the single and concurrent task conditions), $p=1>.05$) was found between the simulated single and dual task situations (phenomenon 12, estimation error= 5.95%).

When the order of the words was randomized but the order of letters in each word remained unchanged, the simulated interkey time did not show significant change compared to that in the normal text typing condition ($t(19998)=-1.60$, $p=.11>.05$) (phenomenon 4). However, when the order of letters within each word was randomized, the simulated average interkey time increased to 354ms (phenomenon 5, estimation error=22%); as the size of the preview window decreased, the simulated interkey time also increased (R square of simulated interkey time is .97, see Figure 2) (phenomenon 6, estimation error = 10.98%). In addition, the simulated interkey time of high-frequency digrams was significantly shorter than that of low-frequency digrams ($t(398)=2.27$, $p=.024<.05$) (phenomenon 8) but no significant difference of simulated interkey time was found between the long and short words ($t(196)=1.45$, $p=.148>.05$) (phenomenon 9). The simulated interkey time of the first keystroke in a word was 14% longer than that of the subsequent keystrokes (phenomenon 10, estimation error=30%).

The simulated movement time and interkey time of the same letter pairs modeled by TYPIST are summarized in Table IV, which shows that interkey time depends on the specific context (phenomenon 11).

3.2 Units of Typing in Transcription Typing

3.2.1 *Simulation Mechanisms.* The six phenomena in this group are modeled with two fundamental mechanisms in the model: entity-based information processing (phenomena 13, 15, 16, 17, 30) and parallel processing (phenomenon 14).

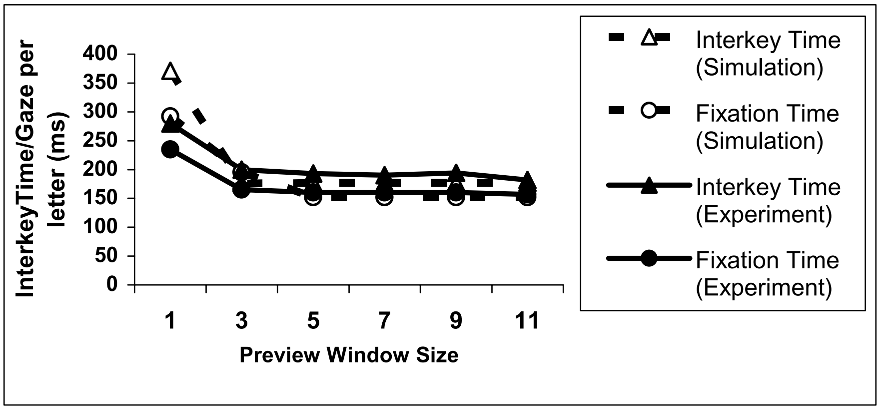


Fig. 2. Comparison of simulated interkey time and gaze duration per character with those of experimental results [Inhoff et al. 1992a; 1992b] in different preview window sizes (unit of size: character).

Table IV. Simulation Results of Interkey Time of the Letter Pairs

Keys	Observed (ms)	Simulation Results		Absolute of relative error %
		Distance (cm)	Interkey time(ms)	
e-e	165	0	165.0	0.00
d-e	201	2	240.2	19.49
c-e	215	4	249.4	16.00
r-e	145	1	151.2	4.26
t-e	159	1.5	154.7	2.70
f-e	168	2	157.7	6.14
g-e	178	3	162.7	8.61
v-e	178	3	162.7	8.61
b-e	195	4	166.9	14.42
Average of relative percentage of error				8.91

(1) Entity-based Information Processing (Phenomena 13, 15, 16, 17, 30). An entity is a basic piece of information processed in the queuing network model, which allows us to observe the activity of entities in the network during the simulation and count the number of these entities in various parts of the network with simple calculations based on the definitions of tying units. According to the definition of copying span, that is, the number of characters typed correctly after an unexpected disappearance of the copy, once the input to the model is suddenly stopped, the total number of entities (characters) held and processed in the model equals copying span and its expected value is 10 characters (phenomenon 13) (see Appendix 5 for its estimation). Moreover, since the visual sampling process defined in the watch for operator allows x characters to enter the model at one time, when the input to the model is suddenly stopped, these x sampled characters are already in the model and thus counted as part of the copying span (see Figure 3). As shown in Figure 3, eye-hand span (the number of characters between the fixation point and the character currently being typed) equals the expected copying span minus the $x/2$ characters on the right side of the fixation point excluding the character being pressed. Given the optimal x value via the optimization process (x_{opt}=4,

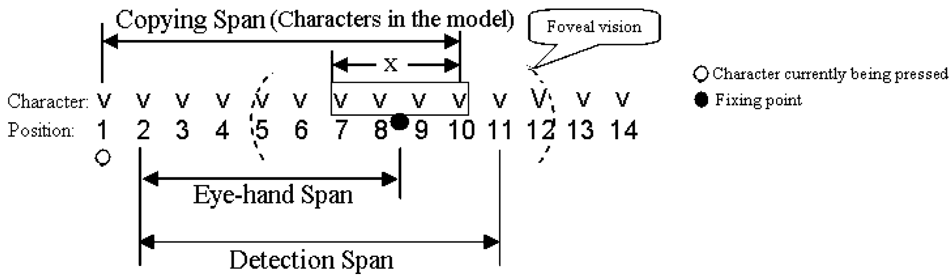


Fig. 3. Graphical illustration of the expected copying span, eye-hand span and detection span.

see Appendix 4), the expected eye-hand span=expected copying span-*x*/2-1=10-4/2-1=7 characters (phenomenon 15). When the text to be typed is composed of random letters, similar to the simulation mechanism of phenomenon 5, the digram frequency effect disappears and each pair of entities takes a longer processing time in the model. Since entities in each subnetwork decay in the model, this reduces the amount of entities held and processed in the model, producing smaller copying spans and eye-hand spans (phenomenon 16). Moreover, when the text to be typed is composed of random letters, the chunk size of each pseudoword decreases, thus increasing the amount of time in perceiving each pseudoword. In addition, as shown in Figure 3, the detection span (characters between the capital character and the character currently being typed) is the sum of the eye-hand span plus the radius of foveal vision excluding the capital character (the central 2 degree vision, 1 degree as radius= 4 characters [Rayner 1998]). Thus, expected detection span=expected eye-hand span+4-1=7+4-1=10 characters (phenomenon 30). Finally, once one of the characters in the text to be typed is suddenly replaced by another character, the model is able to detect this change as long as the entities have not left server Y because server Y is the server for detecting errors and reassembling the motor program in the motor subnetwork. Thus, the total number of entities in the servers after server Y (server Z and the two hand servers) is the replacement span and its expected value equals 3.6 characters (see Appendix 5 for its estimation) (phenomenon 17). In addition, due to the stochastic property of the model (e.g., exponentially distributed processing time of the servers), there are possible differences between these predicted values and simulation results.

(2) Parallel Processing (Phenomenon 14). Similar to phenomenon 12, the queuing network model is able to process the entities representing the stopping span task as well as those of the transcription typing task at the same time. Table V listed the NGOMSL task procedure of the stopping span task as a secondary task. Consistent with the definition of the stopping span, the number of entities typed by the model during the processing period of a tone is regarded as the simulated stopping span.

3.2.2 *Simulation Results.* The simulated average copying span, eye-hand span, and detection span were 9.4, 6.4, and 9.4 characters, respectively (phenomenon 13, estimation error=35.6%; phenomenon 15, estimation error=28%;

Table V. NGOMSL-Style Task Description of Stopping Span Task

GOAL: Do stopping span task
Method for GOAL: Do stopping span task

Step 1. Listen to <the tone> from <the speaker>
Step 2. Retain <the tone>
Step 3. Compare: <the tone> with <the target tone> in memory
Step 4. Decide: If match, then go to step 5
                Else move to step 1
Step 5. Cease //task complete

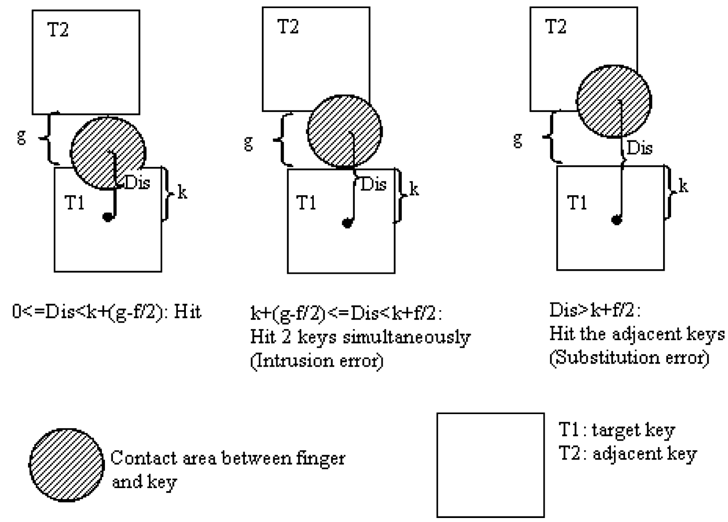
phenomenon 30, estimation error=17.5%). When the text to be typed was composed of random letters, the simulated eye-hand span decreased to 1.4 characters on average (phenomenon 16, estimation error=20%). The simulated average stopping span and replacement span were 2.5 and 3.5 characters, respectively (phenomenon 14, estimation error=15.7%; and phenomenon 17, estimation error=20.7%).

3.3 Errors in Transcription Typing

3.3.1 *Simulation Mechanisms.* The five phenomena in this group are simulated with two mechanisms of the queuing network model: distribution of movement distance and force (phenomena 19, 20, 21) and optimized motor processing (phenomenon 22). Phenomenon 18 can be modeled by the further calculation of simulation results of phenomena 19-22.

(1) Distribution of Movement Distance and Force (Phenomena 19, 20, 21). Based on Tanaka's 1994 equations in quantifying the root-mean-square error (RMSE) of movement directions generated by population vectors in the primary motor cortex, the distribution of movement distance of fingers follows a normal distribution (Dis ∼) (unit: cm) (see its derivation in Appendix 3) which allows the queuing network model to generate intrusion and substitution errors depending on the range of finger movement distance (Dis) in three possible conditions (see Figure 4): i) $0<=Dis<k+(g-f/2)$, when the contact area between a finger and a target key does not contact with the other keys surrounding the target key; ii) $k+(g-f/2)<=Dis<k+f/2$, when this area contacts both the target key and an adjacent key, that is, the finger hits 2 keys simultaneously (intrusion error, phenomenon 20); iii) $Dis>k+f/2$, when this area falls in to the area of an adjacent key but not the target key (substitution error, phenomenon 19).

According to the distribution of the pressing force of fingers (see Appendix 3) and the typical key activation force (0.28 N [Gerard et al. 1999]), the model is also able to generate omission errors in phenomenon 21. The simulated omission errors are categorized into two types. Type A is an omission error which occurs and no simulated finger movement is recorded (the omission error is caused by the failure to preserve sequences in the sensory and working memory), and type B is an omission error which occurs and the movement of a finger is recorded but the simulated finger pressing force on the target key is



g: the average width of gaps between adjacent keys (0.55 cm, measured on a standard QWETY keyboard)

k: half of the average key width (0.65 cm)

f: the average diameter of the finger-key contact area, which equals to the half width of the key (0.65 cm)

Fig. 4. Three possible conditions for the range of finger movements in pressing the target key.

less than 0.28 N (the omission error is caused by an insufficient depression of a keystroke).

(2) Optimized Motor Processing (Phenomenon 22). The coordination of bimanual movements in motor processing is optimized via the optimization of EPD (cross-hand error prevention duration, i.e., waiting for the duration between two entities belonging to different hands, see Appendix 4). In Monte Carlo simulation if EPD is too long, the interkey time becomes very long which deteriorates the typing performance; if EPD is too short, the model has to spend extra time in correcting the typing errors (see Appendix 4).

Since server Y in the queuing network model is able to detect errors via the tactile feedback from the two hand servers and server X, typing errors caused by the hand movements including the deviated movement direction and finger force as well as the insufficient waiting time between the two hands, can be detected without reference to the typed copy. The ratio of typing errors detected without reference to the typed copy over the total number of errors is calculated based on the simulation results of phenomena 19-22 (phenomenon 18).

3.3.2 *Simulation Results.* It was found that in typing 10,000 characters, (1) 41.3% of the substitution errors involved horizontally or vertically adjacent keys (phenomenon 19, estimation error=37.7%); (2) 35.4% of the intrusion errors involved keystrokes with less than 10% of the average interkey time and 57.1% of them involved an adjacent key in the same row or the same column (phenomenon 20, estimation error=6.4%); (3) the average interkey time of the keystrokes right after an omission error occurred was 253ms, which was 1.44 times the simulated average interkey time (176ms) (phenomenon 21, estimation error=6.6%); (4) 68% of the transposition errors were made by the alternate hands (phenomenon 22, estimation error=6.6%). In typing 10,000 characters, 74.5% of the errors were caused by the hand and finger movements and detected without reference of the typed copy (phenomenon 18, estimation error=6.4%).

3.4 Skill Effect in Transcription Typing

3.4.1 *Simulation Mechanisms.* The eight phenomena in this group are modeled by the three general learning mechanisms of the queuing network model described earlier in this article: change of routing probability), optimized motor processing, and general effects of learning.

(1) Change of Routing Probability (Phenomena 24, 25). During the learning process of transcription typing, after entities arrive at server B from the perceptual subnetwork, entities can either take route 1 (go to server C and F for visual guidance and then go to server W without long-term motor program information retrieved from server D) or route 2 (go to server W directly with the long-term motor program information retrieved from server D). At the beginning stage of the learning process, server D has not stored sufficient motor program information and server W is not able to retrieve these motor programs effectively from server D, prolonging the travel time of route 2 and decreasing the routing probability of taking route 2 based on Equation (1). With the number of practice increases, more and more motor programs of digrams as well as the location information of keys are stored at server D. Once the travel time of route 2 decreases with a higher efficiency in retrieving motor program in server D and its value is lower than that of route 1, the majority of entities start to travel via route 2. In other words, at this stage, the model does not have to perform visual search for each digram and the route of visual search (Server C→F→C) is skipped by the majority of entities forming a new route starting from the servers in the visual perceptual subnetwork to Server B→ W→ Y→ Z→ Two Hand Servers. This simulation mechanism is consistent with fMRI studies in transcription typing and other motor control tasks. At the beginning stage of learning, a visuomotor control task including transcription typing mainly activates the DLPFC (dorsal lateral prefrontal cortex) (Server C) and the basal ganglia (Server W) [Jueptner and Weiller 1998; Sakai et al. 1998]. In the well-learned stage (skilled typist in Gordon et al.'s study [1995]), in typing normal texts (multidigit sentence), activation of the DLPFC disappeared and stronger activations were observed in the SMA (supplementary motor area) (Server Y), the basal ganglia (Server W), and the primary motor cortex (M1) (Server Z).

Since the server processing times follow the exponential distribution in QN-MHP [Liu et al. 2006], if $Y_1..Y_k$ are k independent exponential random variables, their sum X follows an Erlang distribution (see Equation (3)). Through rewiring of routes in the learning process, servers C and F are skipped by the majority of entities, that is, parameter k in Equations (4) and (5) decreases. If k' after practice than is smaller k before practice, then the expected overall processing time and its variance decreases, producing phenomena 24 and 25 (see Equation (6)).

$$X = \sum_{i=1}^{k} Yi \tag{3}$$

$$E[X] = E[\sum_{i=1}^{k} Yi] = \sum_{i=1}^{k} E[Yi] = k\frac{1}{\lambda} \tag{4}$$

$$Var[X] = Var[\sum_{i=1}^{k} Yi] = \sum_{i=1}^{k} Var[Yi] = k\frac{1}{\lambda^2} \tag{5}$$

$$If\ k' < k,\ \ then\ E\left[X'\right] < E\left[X\right];\ Var\left[X'\right] < Var\left[X\right] \tag{6}$$

(2) Optimized Motor Processing (Phenomenon 23). Based on the optimization process of the hand and finger movements in the learning process (see Appendix 4), the interkey time of the two-hand (2H) digrams and two-finger (2F) digrams decrease via the optimization of both EPD and 2FC (two-finger coordination time), while the interkey time of the digrams of the one-finger (1F) digrams is reduced only by the optimization of 1FW (one-finger waiting time). Since the sum of the magnitude of EPD and 2FC's reduction is greater than that of 1FW, the model produces phenomenon 23, the reduction of the 2F or 2H digrams' interkey time is greater than that of 1F digrams.

(3) General Effect of the Learning Process (Phenomena 26, 27, 28, 29, 31). The increase in the size of the typing units (copying span, eye-hand span, stopping span, replacement span in phenomena 26-29) is due to several factors in the learning process: (a) the processing speed increases in each server (see Equation (2)); (b) the route of the majority of entities rewires and servers C and F are skipped from the route (see simulation mechanism of phenomena 24 and 25), and this rewiring process reduces the amount of time that each entity spends in the model (see Equation (6) in the simulation mechanism of phenomenon 24); (c) the optimization of the motor process reduces waiting time in movement (see Appendix 4). Since every subnetwork has certain decay functions in the model [Card et al. 1983; Ito 1991], the less time each entity spends in the network, the larger the number of entities held and processed in the model, increasing the value of these typing units (see the simulation mechanism of phenomena in the "units of typing" group) and decreasing the interkey time (phenomenon 31). However, the random effect in the Monte Carlo simulation in the optimization process (see Appendix 4) as well as the stochastic property of the whole model may attenuate the increase of these typing units via the learning process.

3.4.2 *Simulation Results.* The model's simulation of its learning process[1] showed that the simulated tapping rate and the typing speed during the learning process was significantly correlated (Pearson correlation coefficient=0.784, N=8, p =.021<.05) (phenomenon 24). The change of the quartile range (75% quartile-25% quartile) of the interkey time, that is, the inter-keystroke variability, was correlated with the change of the simulated typing speed time with the Pearson correlation coefficient -0.911; the intrakeystroke variability simulated by the model correlated -0.795 with the simulated typing speed (phenomenon 25, estimation error = 22%). The average slope of regression equations relating the simulated digram interval to the simulated typing speed were -2.03 and -1.71 for 2H and 2F digrams respectively, while the average slope of 1F digrams was -1.65 (phenomenon 23, estimation error = 17.9%).

For the eye-hand span, significant correlation between the eye-hand span and the net words-per-minute was found in the simulation results (Pearson correlation coefficient=.721, $N = 8$, $p = .044 < .05$). The eye-hand span of the model increased by 0.87 characters on average with every 20 net words per minute increase in skill level (phenomenon 26, estimation error = 2.6%). For the replacement span, the Pearson correlation coefficient between net words-per-minute and the replacement span was .867 (N=8, p=.005<.01) (phenomenon 27, estimation error = 8.4%). For the copying span, the Pearson correlation coefficient between the simulated copying span and net words-per-minute was 0.704 (N=8, p=.05) (phenomenon 28, estimation error=23.5%). For the stopping span, the correlation efficient between the simulated stopping span and net words-per-minute was 0.868 (Pearson correlation, N=8, p=.004<.05) (phenomenon 29, estimation error=44.6%). After the model finished its learning process, the simulated interkey time reduced from 385 ms to 176 ms, which followed the power law of practice (R square=0.84 with significant correlation, N=8, p =.005 <.01) (phenomenon 31).

3.5 Phenomena in Eye Movements

3.5.1 *Simulation Mechanism.* All three phenomena in this group emerged as the natural outcomes of the queuing mechanism in the queuing network model. First, similar to the simulation mechanism for phenomenon 6, when the preview window size is very small (1 or 2 characters), motor programs of the high-frequency digrams are decomposed, which increases their retrieval time at server W from server D. Since information entities flow in the model in a queuing process, slower information processing in the motor subnetwork, in turn, slows down information processing in the perceptual subnetwork. Therefore, gaze duration per character increases because servers in the visual perceptual subnetwork have to wait for the motor subnetwork to catch up,

[1]The number of keystrokes typed by QN-MHP and the number of training stages in the simulation of all of the 8 phenomena in skill effects were set according to those in Gentner's experimental study [1983]. A total of about 15,000,000 letters were typed in eight training weeks.

producing phenomenon 32, gaze duration per character decreases with an enlarged preview window size.

Second, following the queuing process in visual sampling—the number of entities (the number of chunks c multiplied by the chunk size x) that leave server B at one time determines the number of entities sampled by servers in the visual perceptual subnetwork at one time, the expected saccade size (s) (the number of entities entering the visual perceptual subnetwork at one time) equals the product of c and$x$. Through the optimization process (see Appendix 4), the expected optimal value of c and$x$ is 1 and 4, respectively, indicating that the expected saccade size is 4 characters (phenomenon 33).

Third, the average fixation duration in phenomenon 34 is the average gaze duration per character without the preview window (phenomenon 32) multiplied by the average saccade size (phenomenon 33).

3.5.2 *Simulation Results.* Figure 2 shows the simulated gaze duration per character (R square of the simulated fixation time is .94) (phenomenon 32). The simulated gaze duration per character without the preview window was 136ms on average. The average saccade size generated by the model was 3.18 characters (phenomenon 33, estimation error= 20.5%) and the average fixation duration was 483ms (phenomenon 34, estimation error= 20.8%).

4. DISCUSSION

An important contribution of this current work is the extension of QN-MHP to incorporate a number of fundamental psychological functions that were absent in its earlier version and the application of QN-MHP to model 32 of the 34 transcription typing phenomena. Working as a single cognitive architecture with the same set of assumptions and mechanisms, the queuing network model is able to simulate diverse aspects of human performance in this typical human computer interaction task, namely, interkey time, typing units and spans, errors, skill acquisition, and eye movements. Furthermore, the queuing network model offers an alternative way of understanding the mechanisms of cognition and human-computer interaction.

In terms of cognition, first, the success of modeling many transcription typing phenomena via the queuing mechanism (e.g., phenomena 1, 7, and all of the 3 eye-movement phenomena) provides further support that the queuing network might be one of the basic mechanisms in cognition especially when the tasks involve interactions among different brain regions and body parts. Second, by using one of the unique features of queuing networks, routing probability, the queuing network model is able to quantify the learning process at the behavioral level (phenomena 24 and 25) with its mechanism consistent with the change of different brain activation patterns discovered by neural scientists at the neurological level. Learning is one of the basic mechanisms in cognition as well as human-machine interactions [Braus 2004; Heathcote et al. 2000; Schmidt 1988]. However, learning mechanisms did not exist in the previous version of QN-MHP. These two points are consistent with the findings in neuroscience [Bullock 1968; Eagleman et al. 2004; Smith and Jonides 1998; Taylor et al. 2000; Braus 2004; Chklovskii et al. 2004; Habib 2003].

Table VI. Extension of the Model in Simulating Human Performancen in Inputting Textual Information via Multimodal Human-Computer Interaction

Model Input (source of text)	Model Output devices
• Watching (display) • Listening (speaker) • Thinking (LTDSM)	• Typing (different keyboards) • Handwriting (hand recognition) • Reading aloud (voice recognition)

In terms of human-computer interaction, first, the queuing network model is able to simulate and analyze design concepts related to information processing capacity (e.g., various typing units and spans). Using an intrinsic feature of queuing networks, entity-based information processing, the model is able to not only quantify but also visualize the various spans in typing, which has potential value for HCI interface comparison and analysis. Second, queuing or waiting is part of our intuitive daily experience, both in general and in HCI tasks, and the queuing network model emphasizes the importance of this aspect and explicitly incorporates the queuing process as one of the major mechanisms in human-machine interaction (e.g., in simulating phenomenon 32, the eyes are waiting for the hands to catch up).

In practice, the queuing network model can be applied in the design of user interfaces. For example, by modifying the arrival pattern of stimuli and using appropriate interface modules, the queuing network model can simulate human performance in inputting textual information via multimodal human-computer interfaces. Table VI summarizes the 9 possible combinations of input modalities and output devices (3*3=9) which can be simulated by QN-MHP. On the one hand, text (entities) can be set to arrive at Server 1 (visual modality), Server 5 (auditory modality), or Server C (central executive, arriving from long-term memory Server D or H) for simulating human performance in inputting textual information from these different sources (looking while typing, listening while typing, or thinking while typing). On the other hand, if the interface/device module is replaced by the modules of different keyboards (e.g., changing the distance between different keys) or modules of a handwriting recognizer [Wu et al. 2003] or when the route of entities are changed from the hand servers to the Mouth server, then the model can simulate human performance in typing on different keyboards, handwriting (handwriting recognition), and reading aloud (voice recognition).

Furthermore, QN-MHP is also able to model and generate both mental and motor workload by using the subnetworks' utilization levels as workload indexes [Liu et al. 2006; Wu and Liu 2007]. In the simulation results in modeling the learning phenomena, it was found that the utilization of the cognitive subnetwork is lower than that of the perceptual and motor subnetworks in the well-learned situation of the model. This indicates that the mental workload of skilled typists is mainly allocated at the perceptual and motor subnetworks which is consistent with the experimental results in phenomenon 3, skilled typist can perform reading comprehension (a high level of mental workload at the cognitive subnetwork) and transcription typing at the same time with very little interference. Moreover, server utilizations in the simulation results suggest that the physical workload (utilization) on the left-hand server is significantly higher than that of the right-hand server, and it is also consistent with the experimental results of QWERTY keyboard studies which found that the left hand is used more often than the right hand in typing tasks [Goldstein et al. 1999]. The authors' recent work in modeling driver's workload and performance using QN-MHP provides a detailed description on quantifying mental workload with the queuing network model [Wu and Liu 2007].

In addition, QN-MHP is article related to existing cognitive models and architectures. The queuing network model described in the current paper is based on MHP in terms of its basic layout (perception, cognition and motor components) as well as the setting of servers' processing speeds [Liu et al. 2006]. Therefore, TYPIST and QN-MHP share the same ancestor (MHP); however, QN-MHP and TYPIST use different modeling mechanisms. QN-MHP is a simulation model with queuieng network properties, whereas TYPIST is not a simulation model and it analyzes information processing as PERT scheduling charts. Liu [1996] has shown mathematically that PERT models are a special case of queuing network models.

Currently, QN-MHP has several limitations in modeling various kinds of tasks. First, the tasks modeled by QN-MHP are focused on perceptual-motor tasks; at this stage, QN-MHP has not modeled any high-level cognition phenomena including problem solving, reading comprehension, and complex reasoning. This is also the reason why QN-MHP is not able to quantify the 2 typing phenomena in transcription typing related to reading comprehension. Second, QN-MHP currently uses the NGOMSL method to analyze each task before a model simulation. If the strategies of subjects change, the NGOMSL description needs to be changed, thus constraining the model's ability to quantify individual differences as a function of task strategies.

In summary, our model offers an alternative method in modeling and quantifying a diverse range of phenomena in typing. We are systematically extending the model to cover a broader range of tasks. Our comprehensive computational model of transcription typing offers not only theoretical insights into typing performance, but it is a step toward developing proactive ergonomic design and multipurpose analysis tools for tasks in human-computer interaction.

APPENDIXES

Appendix 1. Derivation of Equation (1)

Equation (1) is derived based on Black's model [1999] as well as other neuroscience findings. Black proposed a model to explain the role of BDNF (brain derived neurotrophic factor) in its regulation of synaptic plasticity in adults BDNF increases the activity of NMDA (N-methyl-D-aspartate) receptors, increases neuron channel open probability by increasing opening frequency, and then increases the velocity of spikes trains travel (V) through these neuron channels. Hence, the stronger synaptic connection strength (the amount of presynaptic transmitter released and the degree of postsynaptic responsiveness) of an individual route, the greater the probability (P_i) that spikes trains

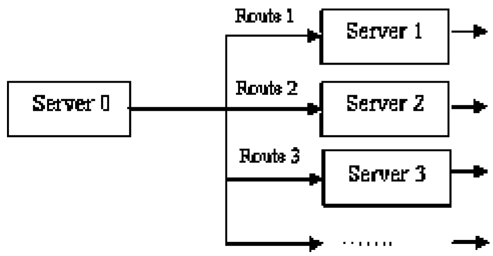


Fig. 5. Multiple routes for one location in queuing network (server 0 has U multiple routes as output).

(represented by entities) travel through that route [Black 1999; Braus 2004; Chklovskii et al. 2004; Habib 2003] (see Equation (7) and Figure 5).

$$Pi = \frac{STi}{\sum_{j=1}^{U} ST_j} \tag{7}$$

In Equation (7), the numerator (ST_i) stands for the standardized synaptic connection strength of route i ($ST_i \in [0, 1]$). The denominator represents the sum of the standardized synaptic connection strength of all the multiple routes starting from the original brain region (server 0 in Figure 5). Moreover, the standardized synaptic connection strength of route i (ST_i) is in direct ratio with the standardized velocity (Vi) that the spikes trains travel through that route [Black 1999; Bullock 1968; Chklovskii et al. 2004] (see Equation (8)).

$$ST_i = r_0 V_i \tag{8}$$

In Equation (8), r_0 is a parameter stands for the ratio between ST_i and V_i.

Since the queuing network is able to capture several properties of information processing in the human brain spikes trains carrying information (represented by entities) travel through different brain regions and form brain traffic, including possible waiting of the previous information flow to be processed (see the first learning mechanism in the queuing network). The travel time of the spikes trains (represented by entities) in route i is composed of both waiting and processing time and therefore this travel time can be regarded as the sum of waiting time (W_i) and processing time (T_i) of entities, That is travel time (S_i) in that route. Furthermore, this travel time (sum of waiting and processing time) is an inverse ratio with the standardized velocity (V_i) of the travel process (see Equation (9)).

$$V_i = \gamma \left(\frac{1}{W_i + T_i} \right) = \frac{\gamma}{S_i} \tag{9}$$

In Equation (9), γ is a parameter represents the inverse ratio between W_i+T_i and Vi.

Combining Equation (7)–(9), Equation (10) and (11) quantify the probability (P_i) that the spikes trains (entities) pass through route i in totally U multiple routes.

$$Pi = \frac{ST_i}{\sum_{j=1}^{U} ST_j} = \frac{r_0 V_i}{\sum_{j=1}^{U} r_0 V_j} = \frac{r_0\left(\frac{\gamma}{S_i}\right)}{\sum_{j=1}^{U}\left[r_0\left(\frac{\gamma}{S_j}\right)\right]} = \frac{1/S_i}{\sum_{j=1}^{U}\frac{1}{S_j}} \tag{10}$$

Thus, we have:

$$P_i = \frac{1/S_i}{\sum_{j=1}^{U}\frac{1}{S_j}} \tag{11}$$

In short, the learning process increases the synaptic connection strength which improves the effectiveness of the information processing of brain regions in the neuron pathway (route) and then changes the probability that the majority of spikes trains (entities) enter one of multiple neuron pathways (routes). If the majority of entities change their route from one to another, rewiring of neuron pathways (routes) occurs.

Appendix 2. Calculation of the Expected Position of the First Character in Each Chunk in a Word

The expected position of the first character in each chunk can be estimated by using the following logic. Suppose the position of characters of a word is starting from 1, based on the definition of different units in typing (see Figure 3), the expected position of the first character in each chunk ($E(FC)$) can be quantified into Equation (12).

$$E(FC) = E(FP) - \left\lceil \frac{x_{opt} - 1}{2} \right\rceil \tag{12}$$

In Equation (12), $E(FP)$ stands for the expected position of the fixation point, and $\left\lceil \frac{x_{opt}-1}{2} \right\rceil$ refers to the half-range of each chunk under extensive practice condition. Since the average word length is 5 characters [John 1988; 1996], the expected fixation point is located at the middle point of the first half of a word (see the simulation mechanism of phenomenon 10), i.e. the second character ($E(FP)$=2). In addition, the optimal chunk size is 4 characters (x_{opt}=4, see Appendix 4). Therefore, $E(FC)$ equals 1 (see Equation (13)), that is the expected position of the first character in each chunk equals the first character in each word in transcription typing.

$$E(FC) = E(FP) - \left\lceil \frac{x_{opt} - 1}{2} \right\rceil = 2 - \left\lceil \frac{4 - 1}{2} \right\rceil = 1 \tag{13}$$

Appendix 3. Processing Logic of Hand and Foot Servers

This section describes the context-free processing logic of the hand and foot servers in detail.

3.1 Hand Servers

The processing logic of hand servers includes three aspects: simulated movement time, distribution of movement distance and the pressing force of the fingers in the hand servers.

3.1.1 *Movement Time.* The simulated movement time of hands including thei fingers is estimated depending on whether the movement is executed with visual guidance or not. If the movement is executed with visual guidance, a variant of Fitt's Law [Welford 1968] is used to estimate the horizontal movement time (MT) of the hands including their fingers (see Equation (14)).

$$MT = I_m log_2(Dis/S + 0.5) \tag{14}$$

In Equation (14), Dis is the movement distance, S refers to the size of a key or button (S =1.3cm for a standard QWERTY keyboard), and I_m is a parameter corresponding to different parts of the hands, for instance, for fingers, I_m=1000/38=26.3 [Langolf et al. 1976].

If the movement can be executed without visual guidance (that is, ballistic movements), e.g., movements in typing after extensive practice, the queuing network model uses the formula proposed by Gan and Hoffman [1988] to estimate the movement time:

$$MT = a + b\sqrt{Dis}, \tag{15}$$

where a and b are constants depending on the number of components in the movement (e.g., a=52.95, b=15.72 for the movement composed of single component).

3.1.2 *Distribution of Movement Distance.* The distribution of movement distance is estimated based on the findings in neurological studies that the movement direction of body parts can be predicted by the action of motor cortical neurons in the primary motor cortex [Georgopoulos et al. 1993]. When individual cells in the primary motor cortex are represented as vectors, they make weighted contributions along the axis of their preferred direction and the resulting vector (population vector) is the sum of all of these cell vectors. Tanaka [1994] quantified the RMSE (room-mean-square error) of the movement direction ($RMSE_\theta$) of a certain body part as a function of the population size (M) of corresponding brain area in the primary motor cortex (see Equation (16)).

$$RMSE_\theta = 97.3M^{-1/2} - 0.1 \tag{16}$$

RMSE in general can be quantified as Equation (17) [Hansen et al. 1953], where refers the difference between the expected value of the sample mean ($\bar{\theta}$) and the true value of $\theta(\bar{\theta})$ (unit of θ is degree).

$$RMSE_\theta = \sqrt{SD_\theta^2 + (\bar{\theta} - \tilde{\theta})^2} \tag{17}$$

According to the law of large numbers in statistics, when the value of the sample size increases to a great value (e.g., sample size>1000), $\bar{\theta}$ is closing to $\tilde{\theta}$, i.e. ($\bar{\theta} - \tilde{\theta} \to 0$). Thus, $RMSE_\theta = \sqrt{SD_\theta^2 + (\bar{\theta} - \tilde{\theta})^2} = \sqrt{SD_\theta^2} = SD_\theta$.

Moreover, since Tanaka [1994] found the distribution of θ follows normal distribution, combining Equation (16) and (17), the distribution of θ can be quantified as Equation (18), where SD_θ stands for the standard deviation of the distribution.

$$\begin{aligned} &\theta \sim N(\bar{\theta}, SD_\theta) \\ &\text{i.e. } \theta \sim N(\bar{\theta}, 97.3M^{-1/2} - 0.1) \end{aligned} \tag{18}$$

Based on Equation (18), given that the movement distance (Dis) is the product of the $2\pi\times$movement radius (RD) and $\theta/360$ (i.e. Dis = $(\theta/360) \times 2\pi$ RD), the distribution of movement distance can be estimated via Equation (19).

$$Dis \sim N\{\overline{Dis}, [(97.3M^{-1/2} - 0.1)/360] \times 2\pi RD\} \tag{19}$$

Based on the value of M measured in neuroscience studies and the value of RD measured in anthropometry studies, Equation (19) can be used to estimate the distribution of movement distance of different body parts including hands and fingers. For example, given that the population size (M) of the brain area corresponding to each finger [M =7300 on average, Reinkensmeyer et al. 2003; Penfield and Rasmussen 1950] and the movement radius (RD) in typing (17.5cm on average, since the hands of the typist are moved to reach different keys with the wrist as an axis and the average distance from the wrist to the tip of fingers is 17.5cm [Armstrong 2004], the distribution of movement distance of each finger on average follows Equation (20).

$$\begin{aligned} &Dis \sim N\{\overline{Dis}, [(97.3 \times 7300^{-1/2} - 0.1)/360] \times 2\pi \times 17.5\} \\ &\text{i.e. } Dis \sim N(\overline{D}is, 0.317) \qquad \text{(unit: cm)} \end{aligned} \tag{20}$$

In other words, since 360 degree of the radius include all of the directions of the movements, it is the radius (the distance a finger moves) that determines whether the errors occur or not and what types of errors would occur (intrusion or substitution).

3.1.3 *Distribution of Finger Pressing Force.* Table VII is directly quoted from Li et al. [2001], which summarized the mean and standard deviation in the distribution of fingers' pressing force (F∼N(M, SD)) in a key pressing task under bilateral multi-finger condition.

The forces of the 8 fingers are implemented in the model's two hand servers as 8 variables which follow the normal distribution with mean and standard deviation in Table VII.

3.2 Foot Server

The foot server executes the simulated movement to press a pedal and its movement time (MT_{foot}) can be estimated by the formula proposed by Drury [1975] (Equation (21)), where S refers to the shoe width [10cm, Armstrong

Table VII. Finger Force and its Variability in a Key Pressing Task

	Right hand				Left hand			
Mean & SD	Little	Ring	Middle	Index	Little	Ring	Middle	Index
M (Newton)	6.2	9.8	18.5	17.4	7.8	9.9	15.1	19.4
SD	2.2	2.5	3.0	2.7	1.8	1.2	3.2	2.8

2004]; W is the pedal width (10cm, same with the shoe width) and A stands for the movement distance (3cm, typical movement distance for a foot pedal).

$$MT_{foot} = (1/1.64)[0.1874 + 0.0854 \times log_2(A/(W + S) + 0.5)] \qquad (21)$$

Appendix 4. Optimization of the Parameters of the Queuing Network

To simulate the trial-and-error learning in the motor learning process, Monte Carlo simulation[2] is performed in server B and Y to find the optimal value of five parameters in the transcription typing task: chunk size (x), number of chunks (c), EPD (cross-hand error prevention duration), 2FC (two-finger coordination time), and 1FW (one-finger waiting time).

4.1 Chunk size (x) and Number of Chunks (c)

In processing the normal text in human-machine interaction (e.g., typing and handwriting), the chunk size (x) and the number of chunks (c) at server B are determined by the optimization process which trades off the time required to correct the wrongly processed entities caused by the failure to preserve the characters at server B with the time saved by increasing the size of each chunk and number of chunks.

Definitions:

x: chunk size x_{opt}: expected optimal chunk size N: total number of entities processed w: overall duration of processing each chunk at servers after server B c: current number of chunks at server B e_{pho}: rate of retrieval failure at server B	R: average duration to correct an error caused by a wrongly processed entity or character N/x: total chunks of a normal text which composed of N entities or characters cx: current number of entities at server B w/x: duration of processing each entity or character w(N/x): overall duration of processing N entities or characters:

[2]The length of the Monte Carlo simulation (number of letters typed by the model) is the same with the approximate number of letters typed during the learning process of typing (10,000,000 letters, [Gentner 1983]) (There are a total of 50 runs for the Monte Carlo simulation.) The random numbers used in each run as the stochastic input to the model are the standard random number series in Promodel software [Promodel 2004].

Objective function:

$$Z = Min\,[w(N/x) + e_{pho}NR] = Min\{N[(w/x) + e_{pho}R]\} \quad (22)$$

$$\text{i.e. } Z' = Min\,[(w/x) + e_{pho}R] \quad (23)$$

One aspect of typing out the chunks and fixing the errors in retrieval of these chunks is the objective function (Equation 22). The task completion time in this function is composed of two parts: a) typing time ($w(N/x)$, that is, the overall duration of processing each chunk at servers (w) multiplied by the total chunks of a normal text which is composed of N (N/x)); b) fixing time (rate of retrial failure of entities (e_{pho}) multiplied by the total number of entities processed and the average duration to correct a wrongly processed entity).

Constraints:

(a) The average preservation duration of each character at server B (B_p) is quantified in Equation (24):

$$B_p = \frac{1}{cx}\sum_{n=1}^{n=cx} n\,(w/x) = 0.5(1 + cx)(w/x) \quad (24)$$

For example, suppose 3 characters (L1, L2, L3) enter server B with order L1 to L3, and the duration of L3 preserved at server B equals (w/x) waiting time for the current character to exit the model so that L3 can enter server W. Similarly, duration of L2 preserved at server B is 2 (w/x) and L1 is 3(w/x). Thus, the average preservation duration of each character is [(1+2+3)/3]$\times$(w/x).

(b) Based on the decay rate of characters at server B [Card et al. 1983]:

i) if $1 \le cx \le 4$ one word condition; average word length is 4 for the most frequent used words in Murdock's experiment [1961]:

$$e_{pho} = .0065 \times 0.5(1 + cx)(w/x) \quad (25)$$

ii) if $5 \le cx \le 8$ (2 words condition, deducted from 1 and 3 words condition):

$$e_{pho} = .0403 \times 0.5(1 + cx)(w/x) + 0.1 \quad (26)$$

iii) if $9 \le cx \le 13$ (3 words condition):

$$e_{pho} = .074 \times 0.5(1 + cx)(w/x) + 0.1 \quad (27)$$

Therefore, the objective functions in three different conditions are:

i) $$\text{if } 1 \le cx \le 4 : Z' = (w/x) + 0.0065 \times 0.5(1 + cx)(w/x)R \quad (28)$$

ii) $$\text{if } 5 \le cx \le 8 : Z' = (w/x) + 0.0403 \times 0.5(1 + cx)(w/x)R + 0.1R \quad (29)$$

iii) $$\text{if } 9 \le cx \le 13 : Z' = (w/x) + 0.074 \times 0.5(1 + cx)(w/x)R + 0.1R \quad (30)$$

In the learning process of the model, the optimal value of c and x are selected via Monte Carlo simulation based on the objective functions in the three different conditions. For example, given the range of w ($.5 \le w \le 5$s) in typing normal text and R=2726ms (determined by simulation results of the model in

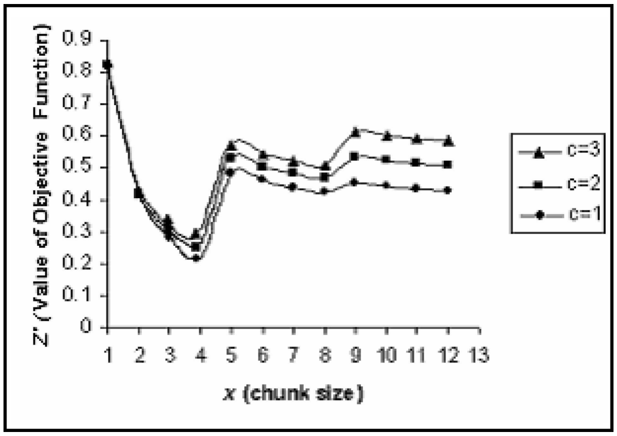


Fig. 6. The change of objective function value (Z') with chunk size (x) and number of chunks (c) (w=0.8s based on the simulation results in typing normal text at well-learned situation; the curves of $c > 3$ conditions are located above the curve c=3 condition, following the same pattern).

correcting a typing error), by simulating the objective functions based on the constraints, we obtained the optimal value of x and $c$in typing condition: c_{opt}=1 chunk, x_{opt}=4 characters (see Figure 6). Based on Equation 25, e_{pho}=0.3 %. In general, Equation (22)–(30) are not task-specific, and they can be applied in modeling other text processing tasks including reading, handwriting, and typing with other keyboards.

4.2 EPD (Cross-Hand Error Prevention Duration)

According to the queuing structure of the two hands, the entities or characters that belong to different hands have to wait EPD to prevent the frequent occurrence of a transposition error, otherwise the transposition error always occurs when the interkey time of the previous keystroke is longer than that of the current keystroke in this 2H situation. The improvement of overlapping movement of the two hands is quantified as the reduction of EPD via its optimization process.

The optimization process of EPD is a trade-off between the time in typing and the time in error correcting that is, reducing the value of EPD causes (1) more efficient overlapping of the movements of the two hands, reducing the interkey time and (2) higher probability in making a transposition error, increasing the time in error correcting. This trade-off can be quantified in the following equations.

The time (Y) saved by optimization of EPD is:

$$Y = N(EPD_0 - EPD) - eNR_t \tag{31}$$

In Equation (31), N is the number of characters typed, e refers to the error rate of the transposition error made by reducing of EPD, R_t specifies how long to correct one transposition error, and EPD_0 is the original value of EPD at beginning of learning.

Hence, the optimization of EPD can be quantified with the following equations:

Objective function:

$$Max(Y) = Max[N(EPD_0 - EPD) - eNR_t] \tag{32}$$

Constraints: e=f (EPD) (f is the function which represents the relationship between EPD and e) (0<= e <=1); 0<=EPD<= 176ms (the maxim value of EPD is lower than one interkey time on average).

Specification of parameters and constraints:

(a) N=1000 characters as the total number of characters in the sample text.
(b) EPD_0 = 354ms as the 2 times of an average interkey time (a sensitivity analysis indicates that this initial value of EPD does not affect simulation results)
(c) R_t = 3112 ms on average which is determined by simulation results of the model in correcting a transposition error.
(d) e=f (EPD), the relationship between e and EPD is set via the curve estimation of the simulation results (R square=.996) (see Equation (33)).

$$e = 0.16 - 0.034ln(EPD) \tag{33}$$

Consequently, the objective function can be simplified into the following Equation (34):

$$\begin{aligned} &Max(Y) = Max[N(EPD_0 - EPD) - eNR_t] \\ &= Max\{1000 \times (354 - EPD) - [0.16 - 0.034ln(EPD)] \times 1000 \times 3122\} \end{aligned} \tag{34}$$

Monte Carlo simulation was performed during the learning process of the model. During the learning process, the value of EPD was updated after typing every 50 characters. A better value of EPD which generated a greater value of Y replaced the original value of EPD and therefore we obtained the optimal value of EPD and its range (EPD_{opt}=108±10ms) to maximize Y value of the objective function (see Figure 7 for the curve of objective function) via the learning process.

4.3 Two-Finger Coordination Time and One-Finger Waiting Time

The value of 2FC (two-finger coordination time) and 1FW (one-finger waiting time) are set based on the similar Monte Carlo simulation logic during the learning process the two parameters are updated during the learning process to minimize the interkey time. The obtained optimal values of the two parameters were 0ms.

Appendix 5. Calculation of the Expected Copying Span and Replacement Span

The copying span and replacement span can be estimated based on the following mechanisms. For the copying span, in the motor subnetwork, since the half-life of entities in the motor subnetwork is 1000ms, the last entity

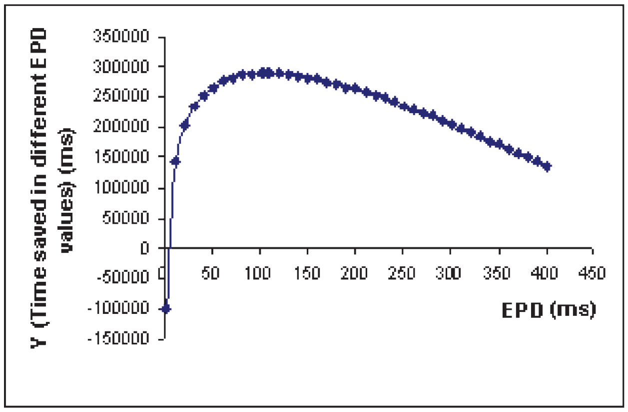


Fig. 7. The relationship of EPD and Y value of the objection function in Monte Carlo simulation results.

in the motor subnetwork decays at the end of the 1000ms with .5 of chance when the input to the model is stopped. Therefore, including this last entity, the total expected number of entities exited from the motor subnetwork is 1000/interval of leaving = 1000/simulated interkey time = 1000/176 $\approx$ 6 entities, that is, the expected number of entities in the motor subnetwork is 6.) In the cognitive subnetwork, only server B is in the route of entities (see simulation mechanism of phenomenon 24 and 25), and it holds 1 chunk (x_{opt}=4 characters, see Appendix 4.) In the perceptual subnetwork, when 4 entities in the motor subnetwork leave the model (it takes 4$\times$176=704ms on average), which allows a chunk to leave server B and entities from the perceptual subnetwork enter server B, all of the entities in the perceptual subnetwork have already decayed since the half-life of information in the perceptual subnetwork is only 200ms. In sum, the expected copying span is 6 characters in the motor subnetwork plus 1 chunk (4 characters) in the cognitive subnetwork, that is, 10 characters.

For the replacement span, the 6 characters in the motor subnetwork are distributed in the 5 servers in the motor subnetwork (server W, Y, Z, and two hand servers) and each server holds or processes 6/5=1.2 characters on average. Accordingly, the expected number of entities in server Z and 2 hand servers is 1.2$\times$3=3.6 characters, that is, the expected replacement span is 3.6 characters.

Appendix 6. Sources of Equations and their Parameters

Table VIII. Equations and Sources of Equations and Parameters

Equations and their Parameters	**Sources of Equations and Parameters**
Equation (1)	Black 1999; Bullock 1968; Chklovskii et al. 2004
Si (Sojourn time of route *i*)	Value obtained during the simulation of the model [sum of waiting time (W_i) and processing time (T_i) of entities, Feyen 2002; Liu et al. 2006]
Equation (2)	Heathcote et al. 2000
$A_{i,}$ (the expected minimal processing time (*Ti*) at server i after intensive practice) B_i(change of expected processing time from the beginning to the end of practice)	Feyen 2002; Liu et al. 2006
α_i (0.001, learning rate of server i)	Heathcote et al. 2000
N_i(10,0000, number of entities processed by server i)	Nelson-Denny Reading Test used (Salthouse's study [1984a, 1984b, 1987])
Equations (3–6)	Gross and Harris 1985; Fundamentals of queueing theory
Equations 3–6 are served to prove the change of expected interkey time and its variation.	
Equations (7–11)	Black 1999; Bullock 1968; Chklovskii et al. 2004
Equations 3–11 are served to derive Equation 1.	
Equations (12–13)	Definition of units of typing [Salthouse 1986a, 1986b, 1984a, 1984b, 1987]
FP (2, expected position of the fixation point in a word)	Rayner 1998
X_{opt} (4, optimal chunk size)	Derived based on Equations (22)–(30) in Appendix
Equation (14)	Welford 1968
Im (26.3, a parameter corresponding to different parts of the hands)	Langolf et al. 1976
Dis (movement distance)	Standard QWERTY keyboard and averaged anthropometric data of hands [Armstrong 2004]
S (1.3 cm, size of each key)	Standard QWERTY keyboard
Equation (15)	Gan and Hoffman 1988

Table VIII. *(Continued)*

Equations and their Parameters	Sources of Equations and Parameters
a=52.95, b=15.72 constants for the movement composed of single component of fingers	Gan and Hoffman 1988
Equations (16–18)	Tanaka 1994; Hansen et al. 1953;
Equations 16–18 are used to develop Equations 19–20	
Equations (19–20)	Equations (16)–(18)
M (7300 clusters, population size (M) of the brain area corresponding to each finger)	Reinkensmeyer et al. 2003; Penfield and Rasmussen 1950
RD (17.5 cm, movement radius)	Armstrong 2004
Equation (21)	Drury 1975
S (10 cm, shoe width), W (10 cm, the pedal width)	Anthropometric data of foot [Armstrong 2004]
A (3 cm, movement distance of foot)	Typical movement distance for a foot pedal. Based a sensitivity analysis, when A varies from 3-10 cm (maximum of foot movement on a pedal), it did not affect the simulation results of current task.
Equations (22–24) See Definition of the parameters in Appendix 4 and their values are set during the optimization process	Developed based on the nature of the composition of task completion time and preservation duration of each character at a server (see paragraph right below those two equations)
Equation (25–34)	Developed based on Equations (22)–(24)

ACKNOWLEDGMENT

We appreciate the very helpful suggestions and comments from the editors and several anonymous reviewers. We also thank Mrs. Bin Lin at East China Normal University who spent time in polishing and editing the manuscript.

REFERENCES

AIZAWA, H., INASE, M., MUSHIAKE, H., SHIMA, K., AND TANJI, J. 1991. Reorganization of activity in the supplementary motor area associated with motor learning and functional recovery. *Experim. Brain Resear. 84*, 3, 668–671.

ALEXANDER, R. M. 1993. Optimization of structure and movement of the legs of animals. *J. Biomechan. 26*, 1–6.

ANDERSON, J. R. AND LEBIERE, C. 1998. *The Atomic Components of Thought*. Lawrence Erlbaum Associates.

ANDERSON, J. R., QIN, Y. L., STENGER, V. A., AND CARTER, C. S. 2004. The relationship of three cortical regions to an information-processing model. *J. Cognit. Neurosci. 16*, 4, 637–653.

ARMSTRONG, T. J. 2004. *Applied Anthropometry*. http://ioe.engin.umich.edu/ioe491Anthrodata.

ASARI, T., KONISHI, S., JIMURA, K., AND MIYASHITA, Y. 2005. Multiple components of lateral posterior parietal activation associated with cognitive set shifting. *Neuroimage 26*, 3, 694–702.

BADDELEY, A. D. 1992. Working memory. *Science, 255*, 5044, 556–559.

BALTES, P. B., STAUDINGER, U. M., AND LINDENBERGER, U. 1999. Lifespan psychology: Theory and application to intellectual functioning. *Ann. Rev. Psych. 50*, 471–507.

BEAR, M. F., CONNORS, B. W., AND PARADISO, M. A. 2001. *Neuroscience: Exploring the Brain*. Lippincott Williams & Wilkins, Baltimore, MD.

BLACK, I. B. 1999. Trophic regulation of synaptic plasticity. *J. Neurobiol. 41*, 1, 108–118.

BOETTIGER, C. A. AND D'ESPOSITO, M. 2005. Frontal networks for learning and executing arbitrary stimulus - Response associations. *J. Neurosci. 25*, 10, 2723–2732.

BOR, D., CUMMING, N., SCOTT, C. E. L., AND OWEN, A. M. 2004. Prefrontal cortical involvement in verbal encoding strategies. *European J. Neurosci. 19*, 12, 3365–3370.

BORGHESE, N. A. AND CALVI, A. 2003. Learning to maintain upright posture: What can be learned using adaptive neural network models? *Adaptive Behav. 11*, 1, 19–35.

BRAUS, D. F. 2004. Neurobiology of learning - The basis of an alteration process. *Psychiatrische Praxis 31*, S215–S223.

BULLOCK, T. 1968. Representation of information in neurons and sites for molecular participation. *Proc. Natl. Acad. Sci. 60*, 4, 1058–1068.

BUSTILLOS, A. T. AND DE OLIVEIRA, P. M. C. 2004. Evolutionary model with genetics, aging, and knowledge. *Physical Rev. 69*, 2.

BUTSCH, R. L. C. 1932. Eye movements and the eye-hand span in typewriting. *J. Educ. Psych. 23*, 104–121.

CARD, S., MORAN, T. P., AND NEWELL, A. 1983. *The psychology of human-computer interaction*. Lawrence Erlbaum, Hinsdale, NJ.

CHKLOVSKII, D. B., MEL, B. W., AND SVOBODA, K. 2004. Cortical rewiring and information storage. *Nature 431*, 7010, 782–788.

COOK, A. S. AND WOOLLACOTT, M. H. 1995. *Motor Control: Theory and Practical Applications*. Williams & Wilkins, Philadelphia, PA.

DRURY, C. G. 1975. Application of Fitt's Law to foot-pedal design. *Human Factors 17*, 368–373.

DURIC, Z., GRAY, W. D., HEISHMAN, R., LI, F. Y., ROSENFELD, A., SCHOELLES, M. J., SCHUNN, C., AND WECHSLER, H. 2002. Integrating perceptual and cognitive modeling for adaptive and intelligent human-computer interaction. *Proceedings of the IEEE 90*, 7, 1272–1289.

EAGLEMAN, D., JACOBSON, J., AND SEJNOWSKI, T. 2004. Perceived luminance depends on temporal context. *Nature 428*, 6985, 854–856.

FAW, B. 2003. Pre-frontal executive committee for perception, working memory, attention, long-term memory, motor control, and thinking: A tutorial review. *Consciousness Cognition 12*, 1, 83–139.

FEYEN, R. 2002. *Modeling Human Performance using the Queuing Network – Model Human Processor (QN-MHP)*. Department of Industrial and Operations Engineering, University of Michigan Press, Ann Arbor, MI.

FEYEN, R. AND LIU, Y. 2001. Modeling task performance using the Queuing Network Model Human Processor (QNMHP). In *Proceedings of the 4th International Conference on Cognitive Modeling*. Lawrence Erbaum Associates.

FISH, L. A., DRURY, C. G., AND HELANDER, M. G. 1997. Operator-specific model: An assembly time prediction model. *Hum. Factors Ergonom. Manufac. 7*, 3, 211–235.

GAN, K. AND HOFFMAN, E. R. 1988. Geometrical conditions for ballistic and visually controlled movment. *Ergonomics 31*, 829–839.

GENOVESIO, A., BRASTED, P. J., MITZ, A. R., AND WISE, S. P. 2005. Prefrontal cortex activity related to abstract response strategies. *Neuron 47*, 2, 307–320.

GENTNER, D. R. 1983. The acquisition of typewriting skill. *Acta Psychologica 54*, 233–248.

GENTNER, D. R. 1987. Timing of skilled motor-performance—Test of the proportional duration model. *Psych. Rev. 94*, 2, 255–276.

GEORGOPOULOS, A. P., TAIRA, M., AND LUKASHIN, A. 1993. Cognitive neurophysiology of the motor cortex. *Science 260*, 5104, 47–52.

GERARD, M., ARMSTRONG, T. J., FRANZBLAU, A., MARTIN, B. J., AND REMPEL, D. M. 1999. The effect of keyswitch stiffness on typing force, finger electromyography, and subjective discomfort. *Amer. Indus. Hygiene Assoc. J. 60*, 762–769.

GHILARDI, M. F., GHEZ, C., DHAWAN, V., MOELLER, J., MENTIS, M., NAKAMURA, T., ANTONINI, A., AND EIDELBERG, D. 2000. Patterns of regional brain activation associated with different forms of motor learning. *Brain Resear. 871*, 1, 127–145.

GOLDSTEIN, M., BOOK, R., ALSIO, G., AND TESSA, S. 1999. Non-keyboard QWERTY touch typing: A portable input interface for the mobile user. In *Proceedings in Human Factors in Computing Systems (CHI)*. 32–39.

GORDON, A. M., LEE, J. H., FLAMENT, D., UGURBIL, K., AND EBNER, T. J. 1998. Functional magnetic resonance imaging of motor, sensory, and posterior parietal cortical areas during performance of sequential typing movements. *Exper. Brain Resear. 121*, 2, 153–166.

GORDON, A. M. AND SOECHTING, J. F. 1995. Use of tactile afferent information in sequential finger movements. *Exper. Brain Resear. 107*, 281–292.

GROSS, D. AND HARRIS, C. M. 1985. *Fundamentals of Queuing Theory*. John Wiley & Sons, New York, NY.

HABIB, M. 2003. Rewiring the dyslexic brain. *Trends Cognitive Sci. 7*, 8, 330–333.

HANSEN, M. H., HURWITZ, W. N., AND MADOW, W. G. 1953. *Sample Survey Methods and Theory*. John Wiley & Sons, Inc., New York.

HEATHCOTE, A., BROWN, S., AND MEWHORT, D. J. K. 2000. The power law repealed: The case for an exponential law of practice. *Psychonomic Bull. Rev. 7*, 2, 185–207.

HERSHMAN, R. L. AND HILLIX, W. A. 1965. Data-processing in typing - typing rate as a function of kind of material and amount exposed. *Hum. Factors 7*, 5, 483–492.

INHOFF, A. W., BRIIHL, D., BOHEMIER, G., AND WANG, J. 1992a. Eye-hand span and coding of text during copytyping. *J. Exp. Psychol.-Learn. Memory Cognition, 18*, 2, 298–306.

INHOFF, A. W., TOPOLSKI, R., AND WANG, J. 1992b. Saccade programming during short duration fixations - an examination of copytyping, letter detection, and reading. *Acta Psychologica, 81* 1, 1–21.

INHOFF, A. W. AND WANG, J. 1992c. Encoding of text, manual movement planning, and eye-hand coordination during copytyping. *J. Exper. Psychol.: Hum. Percep. Perform. 18*, 437–448.

ITO, M. 1991. Short-term retention of a constructed motor program. *Percept. Motor Skill, 72*, 1, 339–347.

JOHN, B. E. 1988. *Contributions to Engineering models of Human-Computer Interaction*. Carnegie-Mellon University Press, Pittsburgh, PA.

JOHN, B. E. 1996. TYPIST: A theory of performance in skilled typing. *Hum.-Comput. Interac. 11*, 4, 321–355.

JOHN, B. E. AND KIERAS, D. E. 1996a. The GOMS family of user interface analysis techniques: comparison and contrast. *ACM Trans. Hum.-Comput. Interac. 3*, 4, 320–351.

JOHN, B. E. AND KIERAS, D. E. 1996b. Using GOMS for user interface design and evaluation: Which technique? *ACM Trans. Hum.-Comput. Interac. 3*, 4, 287–319.

JOHN, B. E. AND NEWELL, A. 1989. Cumulating the science of HCI: From S-R Compatibility to transcription typing. In *Proceedings of Human Factors in Computing Systems (CHI'89)*. 109–114.

JUEPTNER, M. AND WEILLER, C. 1998. A review of differences between basal ganglia and cerebellar control of movements as revealed by functional imaging studies. *Brain 121*, 1437–1449.

JUST, M. A. AND CARPENTER, P. N. 1992. A capacity theory of comprehension: individual differences in working memory. *Psych. Rev. 99*, 122–149.

KAUFER, D. I. AND LEWIS, D. A. 1999. *Frontal Lobe Anatomy and Cortical Connectivity. In The Human Frontal Lobes: Functions and Disorders*. The Gullford Press, New York, NY.

KRAMPE, R. T., RAPP, M. A., BONDAR, A., AND BALTES, R. B. 2003. Allocation of cognitive resources during the simultaneous performance of cognitive and sensorimotor tasks. *Nervenarzt, 74*, 3, 211–218.

LAIRD, J. E., NEWELL, A., AND ROSENBLOOM, P. S. 1987. Soar: An architecture for general intelligence. *Artif. Intell. 33*, 1–64.

LANGOLF, G. D., CHAFFIN, D., AND FOULKE, J. 1976. An investigation of fitts' law over a wide range of movement amplitudes. *J. Motor Behav. 8*, 2, 113–128.

LAUREYS, S., PEIGNEUX, P., PHILLIPS, C., FUCHS, S., DEGUELDRE, C., AERTS, J., DEL FIORE, G., PETIAU, C., LUXEN, A., VAN DR LINDEN, M., CLEEREMANS, A., SMITH, C., AND MAQUET, P. 2001. Experience-dependent changes in cerebral functional connectivity during human rapid eye movement sleep. *Neuroscience 105*, 3, 521–525.

LI, Z. M., ZATSIORSKY, V. M., LI, S., DANION, F., AND LATASH, M. L. 2001. Bilateral multifinger deficits in symmetric key-pressing tasks. *Exper. Brain Resear. 140*, 86–94.

LIM, J. AND LIU, Y. 2004. A queueing network model for eye movement. In *Proceedings of the 2004 International Conference on Cognitive Modeling*. Pittsburg, PA. 154–159.

LIU, Y., FEYEN, R., AND TSIMHONI, O. 2006. Queueing network-model human processor (QN-MHP): A computational architecture for multitask performance. *ACM Trans. Hum.-Compu. Interac. 13*, 1, 37–70.

LIU, Y. L. 1996. Queuing network modeling of elementary mental processes. *Psychol. Rev. 103*, 1, 116–136.

LIU, Y. L. 1997. Queuing network modeling of human performance of concurrent spatial and verbal tasks. *IEEE Trans. Syst. Man Cybernetics Part A-Syst Hum. 27*, 2, 195–207.

LOGAN, G. D. 1982. On the ability to inhibit complex movements - a stop-signal study of typewriting. *J. Exper. Psych.-Hum. Percept. Perform. 8*, 6, 778–792.

MCINTOSH, A. R. 1999. Mapping cognition to the brain through neural interactions. *Memory 7*, 5-6, 523–548.

MCINTOSH, A. R. 2000. Towards a network theory of cognition. *Neural Netw. 13*, 8-9, 861–870.

MEYER, D. E. AND KIERAS, D. E. 1997a. A computational theory of executive cognitive processes and multiple-task performance.1. Basic mechanisms. *Psychol. Rev. 104*, 1, 3–65.

MEYER, D. E. AND KIERAS, D. E. 1997b. A computational theory of executive cognitive processes and multiple-task performance.2. Accounts of psychological refractory-period phenomena. *Psychol. Rev. 104*, 4, 749–791.

MITZ, A. R., GODSCHALK, M., AND WISE, S. P. 1991. Learning-dependent neuronal-activity in the premotor cortex - activity during the acquisition of conditional motor associations. *J. Neurosci. 11*, 6, 1855–1872.

MURATA, A. 1996. Empirical evaluation of performance models of pointing accuracy and speed with a PC mouse. *Int. J. Hum.-Comp. Interact. 8*, 4, 457–469.

MURDOCK, B. B. 1961. The retention of individual items. *J. Exper. Psychol. 62*, 618–625.

MUSTOVIC, H., SCHEFFLER, K., DI SALLE, F., ESPOSITO, F., NEUHOFF, J. G., HENNIG, J., AND SEIFRITZ, E. 2003. Temporal integration of sequential auditory events: silent period in sound pattern activates human planum temporale. *Neuroimage, 20*, 1, 429–434.

NAKAMURA, K., SAKAI, K., AND HIKOSAKA, O. 1998. Neuronal activity in medial frontal cortex during learning of sequential procedures. *J. Neurophys. 80*, 5, 2671–2687.

NAZIR, T. A., BEN-BOUTAYAB, N., DECOPPET, N., DEUTSCH, A., AND FROST, R. 2004. Reading habits, perceptual learning, and recognition of printed words. *Brain Lang. 88*, 3, 294–311.

NAZIR, T. A., DECOPPET, N., AND AGHABABIAN, V. 2003. On the origins of age-of-acquisition effects in the perception of printed words. *Dev. Sci. 6*, 2, 143–150.

NEWELL, A. 1973. You can't play 20 questions with nature and win. Projective comments on the papers of the symposium. In Visual Information Processing, Chase, W. G., ED., Academic Press, New York, NY.

NEWELL, A. 1990. Unified Theories of Cognition. Harvard University Press, Cambridge, MA.

OLSON, J. R. AND OLSON, G. M. 1990. The growth of cognitive modeling in human-computer interaction since GOMS. *Hum.-Comput. Interact. 5*, 221–265.

PEARSON, R. AND VAN SCHAIK, P. 2003. The effect of spatial layout of and link colour in Web pages on performance in a visual search task and an interactive search task. *Int. J. Hum.-Comput. Stud. 59*, 3, 327–353.

PENFIELD, W. AND RASMUSSEN, T. 1950. *The Cerebral Cortex of Man: A Clinical Study of Localization of Function*. Macmillar, New York, NY.

PETERSEN, S. E., VAN MIER, H., FIEZ, J. A., AND RAICHLE, M. E. 1998. The effects of practice on the functional anatomy of task performance. *Proc. Natl. Acad. Sci. 95*, 3, 853–860.

PROMODEL. 2004. *Promodel User Guide*. Promodel Inc., Orem, UT.

RAYNER, K. 1998. Eye movements in reading and information processing: 20 years of research. *Psychol. Bull. 124*, 3, 372–422.

REINKENSMEYER, D. J., IOBBI, M. G., KAHN, L. E., KAMPER, D. G., AND TAKAHASHI, C. D. 2003. Modeling reaching impairment after stroke using a population vector model of movement control that incorporates neural firing-rate variability. *Neural Comput. 15*, 11, 2619–2642.

ROLAND, P. E. 1993. Brain activation. Wiley-Liss, New York, NY.

ROLLS, E. T. 2000. Memory systems in the brain. *Annu. Rev. Psychol. 51*, 599–630.

ROTHKOPF, E. Z. 1980. Copying span as a measure of the information burden in written language. *J. verbal learn. Verbal Behav. 19*, 5, 562–572.

ROUSE. 1980. *Systems Engineering Models of Human-Machine Interaction*. North Holland, New York.

RUDELL, A. P. AND HU, B. 2001. Does a warning signal accelerate the processing of sensory information? Evidence from recognition potential responses to high and low frequency words. *Int. J. Psychophysiol. 41*, 1, 31–42.

RUMELHART, D. E. AND NORMAN, D. A. 1982. Simulating a skilled typist - a study of skilled cognitive-motor performance. *Cogn. Sci. 6*, 1, 1–36.

SADATO, N., IBANEZ, V., CAMPBELL, G., DEIBER, M.P., LEBIHAN, D., AND HALLETT, M. 1997. Frequency-dependent changes of regional cerebral blood flow during finger movements: Functional MRI compared to PET. *J. Cereb. Blood Flow Metab. 17*, 6, 670–679.

SAKAI, K., HIKOSAKA, O., MIYAUCHI, S., TAKINO, R., SASAKI, Y., AND PUTZ, B. 1998. Transition of brain activation from frontal to parietal areas in visuomotor sequence learning. *J. Neurosci. 18*, 5, 1827–1840.

SALTHOUSE, T. 1983. Why is typing rate unaffected by age. *Gerontologist 23*, 68–68.

SALTHOUSE, T. A. 1984a. Effects of age and skill in typing. *J. Exp. Psychol. 113*, 3, 345–371.

SALTHOUSE, T. A. 1984b. The skill of typing. *Sci. Am. 250*, 2, 128–135.

SALTHOUSE, T. A. 1985. Anticipatory processing in transcription typing. *J. Appl. Psychol. 70*, 2, 264–271.

SALTHOUSE, T. A. 1986a. Perceptual, cognitive, and motoric aspects of transcription typing. *Psychol. Bull. 99*, 3, 303–319.

SALTHOUSE, T. A. 1986b. Effects of practice on a typing-like keying task. *Acta Psychol. 62*, 2, 189–198.

SALTHOUSE, T. A. AND SAULTS, J. S. 1987. Multiple Spans in Transcription Typing. *J. Appl. Psychol. 72*, 2, 187–196.

SALVUCCI, D. D. 2005. A multitasking general executive for compound continuous tasks. *Cogn. Sci. 29*, 457–492.

SCHMIDT, R. A. 1988. Motor Control and Learning. Human Kinetics Publishers, Champaign, IL.

SCHMUCK, P. AND WOBKENBLACHNIK, H. 1996. Behavioral flexibility and working memory. *Diagnostica 42*, 1, 47–66.

SHAFFER, L. H. 1975. Control processes in typing. *Q. J. Exp. Psychol. 27*, 419–432.

SMITH, E. E. AND JONIDES, J. 1998. Neuroimaging analyses of human working memory. *Proc. Natl. Acad. Sci.* 95, 12061–12068.

STEYVERS, M., ETOH, S., SAUNER, D., LEVIN, O., SIEBNER, H. R., SWINNEN, S. P., AND ROTHWELL, J. C. 2003. High-frequency transcranial magnetic stimulation of the supplementary motor area reduces bimanual coupling during anti-phase but not in-phase movements. *Exp. Brain Res. 151*, 3, 309–317.

TANAKA, S. 1994. Numerical study of coding of the movement direction by a population in the motor cortex. *Biol. Cybern. 71*, 6, 503–510.

TAYLOR, J., HORWITZC, B., SHAHA, N. J., FELLENZB, W. A., MUELLER-GAERTNERA, H.-W., AND KRAUSEE, J. B. 2000. Decomposing memory: functional assignments and brain traffic in paired word associate learning. *Neural Netw. 13*, 923–940.

TERZUOLO, C. A. AND VIVIANI, P. 1979. The central representation of learned motor patterns. In R. Talbot & D. R. Humphrey Eds., *Posture and Movement*, Raven Press, New York, NY.

TERZUOLO, C. A. AND VIVIANI, P. 1980. Determinants and characteristics of motor patterns used for typing. *Neurosci. 5*, 1085–1103.

VAN MIER, H., TEMPEL, L. W., PERLMUTTER, J. S., RAICHLE, M. E., AND PETERSEN, S. E. 1998. Changes in brain activity during motor learning measured with PET: Effects of hand of performance and practice. *J. Neurophysio. 80*, 4, 2177–2199.

WELFORD, A. T. 1968. Fundamentals of skill. Methuen, London, UK.

WU, C. AND LIU, Y. 2004. Modeling Psychological Refractory Period (PRP) and Practice Effect on PRP with Queuing Networks and Reinforcement Learning Algorithms. In *Proceedings of the 6th International Conference on Cognitive Modeling (ICCM'04)*. Pittsburgh, PA, 320–325.

WU, C., ZHANG, K., AND HU, Y. 2003. Human performance modeling in temporary segmentation Chinese character handwriting recognizers. *Int. J. Hum. Comput. Stud. 58*, 483–508.

WU, C. AND LIU, Y. 2006a. Queuing network modeling of a real-time psychophysiological index of mental workload—P300 amplitude in event-related potential (ERP). In *50th Annual Conference of the Human Factors and Ergonomics Society*. San Francisco, CA.

WU, C. AND LIU, Y. 2006b. Queuing network modeling of age differences in driver mental workload and performance. In *50th Annual Conference of the Human Factors and Ergonomics Society*. San Francisco, CA.

WU, C. AND LIU, Y. 2006c. Queuing network modeling of driver workload and performance. In *50th Annual Conference of the Human Factors and Ergonomics Society*. San Francisco, CA.

WU, C. AND LIU, Y. 2007. Queuing Network Modeling of Driver Workload and Performance. *IEEE Trans. Intell. Transport. Sys. 8*, 3, 528–537.

Received October 2005; revised February 2007; accepted October 2007 by Shumin Zhai