International Journal of Gerontology 18 (2024) 64–69
https://doi.org/10.6890/IJGE.202404_18(2).0001

International Journal of Gerontology

journal homepage: http://www.sgecm.org.tw/ijge/

Review Article

Do Individuals with Mild Cognitive Impairment and Healthy Aging People Have Different Keystroke Dynamics? A Systematic Review

Si-An Lee [a], Jin-Hyuck Park [b] *

[a] *Department of ICT Convergence, The Graduate School, Soonchunhyang University, Asan, Republic of Korea,* [b] *Department of Occupational Therapy, College of Medical Science, Soonchunhyang University, Asan, Republic of Korea*

ARTICLE INFO

Accepted 1 February 2024

Keywords:
digital technology,
cognitive dysfunction,
biomarkers,
systematic review

SUMMARY

This systematic review examined differences in keystroke dynamics between individuals with mild cognitive impairment (MCI) and healthy aging people. A search of Embase, Medline, PsychInfo, PubMed, Web of Science, Google Scholar, and Cochrane Library from 2012 to June 2023 identified 4,847 articles. After removing duplicates, 4,260 articles were screened based on abstract and title alone, resulting in 208 articles for assessing eligibility. Out of these 208 articles, five fully satisfied the inclusion and exclusion criteria of this study. Each showed the feasibility of pause-related keystroke dynamics to differentiate MCI from healthy aging as well as conventional neuropsychological assessments. However, the optimal feature across keystroke dynamics could not be determined due to inconsistency in the analysis of the five studies. Future studies should employ receiver operating characteristic curve analysis with a variety of keystroke dynamics to determine if keystroke dynamics could be a potential surrogate for existing neuropsychological assessments.

1. Introduction

Mild cognitive impairment (MCI), a preclinical stage of Alzheimer's disease (AD), represents a pathological state beyond normal aging, leading to memory and executive dysfunction.[1] The significance of early intervention in AD need to monitor the transition from MCI to AD stage.[2–4] To date, it has primarily relied on conventional neuropsychological assessments in clinics. Unfortunately, these assessments generally often lack sensitivity in differentiating MCI from healthy aging.[2–4]

In addition to cognitive decline, motor decline in patients with MCI has been consistently reported.[5] In a previous study, it was confirmed that poor performance in a motor task could serve a marker to distinguish MCI from normal aging, demonstrating a sensitivity of over 80% and a specificity of over 70%.[6,7] This finding holds significant clinical implications considering that the Montreal Cognitive Assessment (MoCA), a typical screening tool for MCI, has a specificity of less than 80%.[3]

Digital biomarkers using motor function-related data derived from mobile devices have shown great promise.[8,9] From this perspective, changes in typing and touching a computer keyboard or smartphone have been examined and found to be significantly different between individuals with MCI and healthy aging people.[7,10] Specifically, keystroke dynamics such as typing speed and remove rate are significantly correlated with cognitive performance, identified as biomarkers of cognitive decline.[7,10–12] A previous study reported the possibility of distinguishing patients with MCI with more than 80% accuracy using the time to press and release a button,[10] while another study showed the potential of using overall keystroke speed and length of characters typed to discriminate MCI, achieving a sensitivity of 89% and a specificity of 78%.[7]

However, most previous studies have employed different keystroke dynamics, limiting our understanding of the optimal digital marker.[10,12] Additionally, there is no consensus on the duration over which keystroke dynamics should be collected. Consequently, there is a lack of fundamental information to effectively utilize keystroke dynamics as a digital biomarker for MCI. Therefore, this study performed a systematic review of the literature to provide information for the high ecological validity of utilizing keystroke dynamics as biomarkers for MCI, specifically examining their discriminant power.

2. Methods

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). This study was prospectively registered at PROSPERO (ID: CRD42023451551).

2.1. Search strategy and study selection

A literature search was completed on September 4, 2023, covering Embase, Medline, PsychInfo, PubMed, Web of Science, Google Scholar, and Cochrane Library. The search aimed to identify relevant literature on keystroke dynamics for MCI and healthy aging, spanning the period from 2012 to June 2023. The following keywords were used: mobile device OR digital device OR smartphone OR computer OR table AND keystroke OR keyboard OR key button OR key AND detection OR classification OR discrimination OR screening AND

* Corresponding author.
E-mail address: roophy@naver.com (J.-H. Park)

mild cognitive impairment OR neurocognitive disorder OR cognitive decline. Inclusion criteria were limited to studies published in English or Korean.

The initial eligibility screening was independently conducted by two reviewers, who assessed titles and abstracts of the identified studies. Any disagreements between the two reviewers were resolved through discussion with a third-party expert.

2.2. Inclusion and exclusion criteria

This systematic review included studies that examined the impact of MCI on keystroke dynamics. Keystroke dynamics, as per the definition established in a previous study,[10] were considered to encompass keystroke timing information and typing metadata. This includes sequences of timestamps of key presses and releases, as well as the number of characters typed, gathered from various devices such as mobile devices, tablets, computer keyboards, smartphones, and so forth. There were no restrictions on the methods employed for collecting keystroke dynamics. Studies that reported differences in keystroke dynamics between normal aging subjects and patients with MCI were included. Studies that enrolled healthy controls and patients diagnosed with MCI were included.

Conversely, studies that investigated the feasibility of keystroke dynamics without statistical analysis, with or without classification, were excluded. Additionally, studies exclusively focused on the developing software or applications to capture keystroke dynamics were excluded. Grey literature, including unpublished data, conference proceedings, and dissertations, was also excluded. Two reviewers independently applied the inclusion and exclusion criteria to each study and then finally selected studies.

2.3. Quality assessment of evidence

To assess methodological quality, the quality assessment tool adopted from the National Institutes of Health/National Heart, Lung, and Blood Institute was used considering that this systematic review included prospective cohort studies. After answering 14 questions of the tool, the quality of each study was estimated as poor (0–4 out of 14), fair (5–10 out of 14), or good (11–14 out of 14) in accordance with a previous study (Table 1).[13] Detailed criteria were presented in Supplementary Material 1.

2.4. Data extraction

Two authors extracted data from the finally selected studies. The extracted features from studies included were as follows: (1) first author and publication year, (2) general characteristics of participants in individuals with MCI and healthy controls, (3) diagnostic methods, (4) experimental protocol of data collection such as collection setting and duration, (5) keystroke dynamics features, and (5) statistical results (*t*-value, accuracy, sensitivity, specificity, or area under the receiver operating characteristics curve). Any disagreements between the two reviewers were resolved through discussion.

3. Results

3.1. Study selection

The PRISMA flow chart for the study selection process is presented in Figure 1. A total of 4,847 articles were identified from the initial database searches. After removing duplicates, titles and abstracts of the remaining 4,260 articles were reviewed by two independent reviewers for preliminary screening. Of these, five articles that met the inclusion criteria were finally selected.

3.2. Characteristics of included studies

A total of 157 subjects, ranging in ages from 66.2 to 81.12 years, were included. To compare differences in keystroke dynamics between healthy controls and patients with MCI, age-matched subjects with normal aging were selected from the included studies, with the exception of one study that did not provide information on the ages of subjects. Patients with MCI in the included studies were diagnosed according to Petersen's criteria, except for one study that did not report the selection criteria. In addition to the presence or absence of cognitive impairment, the inclusion criteria also consider typing experience, specifying that subjects had used a smartphone or computer for at least a year, or were regular users who used them at least once a week (Table 2).

3.3. Keystroke dynamics

Only one study collected keystroke dynamics in-the-clinic, while

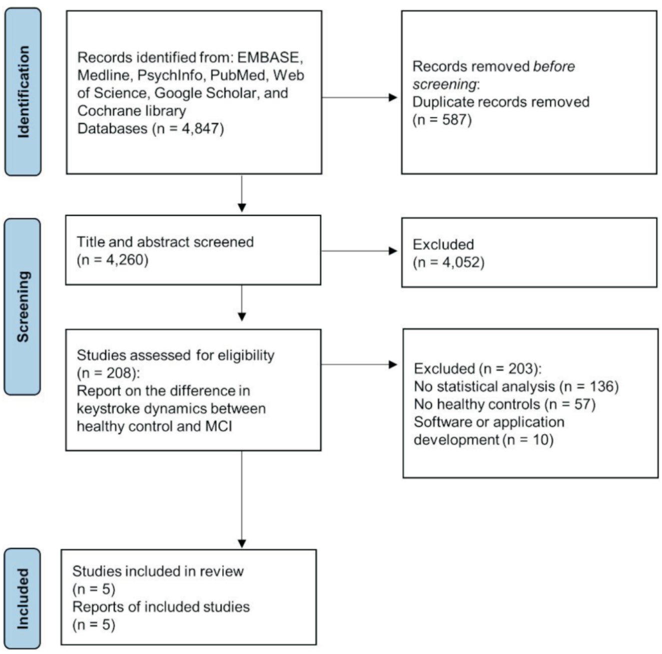

Figure 1. Flow chart of the study selection process.

Table 1
Single-hierarchy evidence model.

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Quality
Vizer et al., 2015[11]	O	O	O	O	X	O	O	NA	O	X	O	NA	O	X	Fair
Stringer et al., 2018[7]	O	O	O	O	X	O	O	NA	O	X	O	NA	O	X	Fair
Ntracha et al., 2020[10]	O	O	O	O	X	O	O	NA	O	X	O	NA	O	X	Fair
Waes et al., 2017[14]	O	X	O	O	X	O	O	NA	O	X	O	NA	O	X	Fair
Stringer et al., 2023[15]	O	O	O	O	X	O	O	NA	O	X	O	NA	O	X	Fair

Table 2
Characteristics of the studies included in the systematic review and meta-analyses.

Author and year	Subjects	Typing experience	Setting	Duration	Keystroke features	Comparison	Statistical analysis	Results
Vizer et al., 2015[11]	HC N: 21 Mean age: 79.2 MCI (Peterson) N: 17 Mean age: 81.1	At least one year	In-the-wild	4 sessions lasting 20 to 45 minutes	Device: desktop computer keyboard Capture: Specially developed recording software Types: total duration, timer per key, pause rate, pause duration, keystroke rates	Linguistic features	ROC curve	[Keystroke dynamics] AUC: NS (p = 0.058) [Linguistic features] AUC: NS (p = 0.40)
Stringer et al., 2018[7]	HC N: 24 Mean age: 71.0 MCI (Peterson) N: 17 Mean age: NS	Regular computer users (defined as using a laptop or desktop at least once a week)	In-the-wild or In-the-clinic	Single session lasting approximately 2 hours	Device: desktop computer keyboard Capture: specially developed recording software Feature: number of pauses per min, keystroke per min	ACE-III Ecog scale TMT-B	ROC curve	[Keystroke dynamics] AUC: 0.80 to 0.91 Sensitivity: 0.84 to 0.89 Specificity: 0.66 to 0.78 [ACE-III] AUC: 0.85 Sensitivity: 0.81 Specificity: 0.87 [Ecog] AUC: 0.82 Sensitivity: 0.95 Specificity: 0.62 [TMT-B] AUC: 0.83 Sensitivity: 0.90 Specificity: 0.62
Ntracha et al., 2020[10]	HC N: 12 Mean age: 66.2 MCI (NS) N: 11 Mean age: 67.2	At least one year	In-the-wild	6 months	Device: smartphone touch keyboard Capture: commercial app ("type of mood") Feature: time per key, pause duration	Linguistic features	ROC curve k-Nearest Neighbors Logistic Regression Random Forest Convolutional Neural Networks	[Keystroke dynamics] AUC: 0.63 to 0.86 Sensitivity: 0.60 Specificity: 0.90 [Linguistic features] AUC: 0.60 Sensitivity: 0.40 Specificity: 0.80 [Ensemble model] AUC: 0.65 to 0.75 Sensitivity: 0.40 to 0.60 Specificity: 0.90
Waes et al., 2017[14]	HC N: 20 Mean age: NS MCI (Peterson and DSM-IV) N: 12 Mean age: NS	Basic computer keyboarding skills (NS for periods)	In-the-clinic	Single session lasting approximately 15 min	Device: desktop computer keyboard Capture: commercial software (Inputlog) Feature: pause duration	None	ANOVA	F-value: 25.4 to 35.7 (p < 0.001) MCI patients revealed longer pause time than healthy controls

Table 2. Continued.

Author and year	Subjects	Typing experience	Setting	Duration	Keystroke features	Comparison	Statistical analysis	Results
Stringer et al., 2023[15]	HC N: 12 Mean age: 66.2 MCI (Peterson) N: 11 Mean age: 67.2	Regular computer users (defined as using a laptop or desktop at least once a week)	In-the-wild	7 to 9 months	Device: smartphone touch keyboard Capture: specially developed recording software (Software Architecture for Mental Health Self-Management, SAMS) Feature: time per key	ACE-III Doors and People Test DSB test FCRST Ecog scale FCRST Stroop test TMT A/B	Regression analysis	[Keystroke dynamics] β-value: 0.63 ($p < 0.001$) MCI patients had slower keystroke speed than healthy controls [ACE-III] β-value: 5.85 ($p < 0.01$) [Doors and people] β-value: 6.76 ($p = 0.003$) [DSB] β-value: 1.92 ($p = 0.013$) [FCRST] β-value: 7.55 ($p = 0.032$) [Stroop] β-value: -5.11 ($p = 0.014$) Only significant comparisons were presented.

ACE: Addenbrooke's Cognitive Examination; DSB; Digit Span Backwards; Ecog: Everyday Cognition; FCRST: Free and Cued Selective Reminding Test; TMT: Trails Making Test Part.

the remaining studies gathered data in-the-wild. Three studies used a desktop computer keyboard, and two studies utilized a smartphone touch keyboard. To capture keystroke dynamics, two studies used commercial software (“Inputlog”) or an application (“Type of Mood”), while three studies used specially developed software or applications (Table 2).

Types of keystroke dynamics varied among the included studies, but all studies except one included at least one feature related to “pause”. Specifically, features such as pause rate, pause duration, and number of pauses per minute were common across the included studies. Additionally, time per key, keystroke rate, and keystroke per minute were captured (Table 2).

The collection period for keystroke dynamics varied from 15 minutes to 9 months. Two studies collected data for a single session lasting from 15 minutes to 2 hours, one study collected for four sessions lasting 20 to 45 minutes, and two studies collected data for more than six months (Table 2).

3.4. Comparisons

In addition to keystroke dynamics, various paper-and-pencil-based neuropsychological assessments were used to identify differences between healthy controls and individuals with MCI (Table 2). Specifically, the Addenbrooke’s Cognitive Examination (ACE)-III as a screening tool assessing global cognitive function was included in two studies. On the other hand, the majority of neuropsychological assessments were memory test tools (e.g., Hopkins Verbal Learning Test and Doors and People test) and executive function test tools (e.g., Trail Making Test Part B and Stroop test). Two studies compared linguistic features in written texts with keystroke dynamics (Table 2).

3.5. Main outcomes

To assess the discriminant power, three studies used the receiver operating characteristic (ROC) curve, one study used analysis of variance, and another study used regression analysis (Table 2). In the two studies using the ROC curve, keystroke dynamics achieved an area under the curve (AUC) value ranging from 0.75 to 0.91, with sensitivity from 0.60 to 0.81 and specificity from 0.66 to 0.90. In these two studies, keystroke dynamics achieved a higher AUC than comparisons. These studies suggested that keystroke dynamics outperformed other comparisons, indicating better discrimination for MCI (Table 2). One study, not reporting detailed statistical values for the ROC curve, suggested that keystroke dynamics showed a more substantial improvement in discriminant power than linguistic features, though not statistically significant.

On the other hand, two studies not using use the ROC curve reported statistical differences in keystroke dynamics or comparisons. One study found that patients with MCI had longer pause time than healthy controls (F: 25.4 to 35.7, $p < 0.001$).[14] Another study found that individuals with MCI had significantly slower keystroke speeds than healthy controls (β: 0.63, $p = 0.001$) (Table 2).[15]

4. Discussion

In this systematic review, distinctions in keystroke dynamics between individuals with MCI and those with normal aging were explored. Among the 208 articles reviewed, five met the inclusion criteria, demonstrating the potential of pause-related keystroke dynamics to differentiate MCI from healthy aging as a surrogate of conventional neuropsychological assessments. However, details regarding sample size, study design, specific keystroke dynamics, comparisons were not consistently presented, leaving uncertainty about the optimal feature across keystroke dynamics due to disparities in the analysis of the five studies.

The eligibility criteria for collecting keystroke dynamics included using a smartphone or computer at least once a week or for at least a year, ensuring that subjects were already familiar with their use. This approach aimed to enable the production of keystroke dynamics in a familiar context, minimizing the need for subjects to make an additional cognitive effort to memorize key sequences. This is consistent with the purpose of collecting keystroke dynamics to identify motor decline rather than pure cognitive decline.[7,10,11,14,15]

Data on keystroke dynamics were predominantly collected more in-the-wild than in-the-clinic, with the aim of gathering information over an extended period. In contrast, two of the included studies that collected keystroke dynamics in-the-clinic completed the collection in a single session. Four out of the five studies collected keystroke dynamics in-the-wild for over sixmonths, aligning with the findings of a previous study showing that, when capturing keystroke dynamics in-the-wild,[16] a longer measurement period, as opposed to a shorter one, might better capture the subjects' original characteristics due to variability over time. Therefore, a collection period of more 6 months in-the-wild is deemed necessary.

Three studies used a study-specific app or software developed, while the other two used commercially available options. There were no significant differences in keystroke dynamics features between the collection methods. However, pause-related features were common across the four studies. Pause, occurring when cognitive demands surpass a subject's cognitive capacity, reflect a decline in working memory, particularly in the prefrontal cortex. A decrease in the ability of working memory to produce the next character or word can lead to more frequent or longer pauses.[17,18] MCI, characterized by reduced prefrontal cortex function, results in decreased working memory,[19] impacting tasks like writing or typing that require visuomotor skills.[20] As a result, pause emerged as a crucial feature in keystroke dynamics for discriminating MCI.

Additionally, keystroke dynamics were found to be effectively distinguish MCI, aligning with traditional neuropsychological assessments.[7,10] This is consistent with the findings of previous studies showing that patients with MCI have not only pure cognitive dysfunction but also motor dysfunction.[21] Specifically, motor dysfunction in MCI more significantly affects fine motor skills than gross motor skills, leading to poorer performance on hand dexterity tasks such as typing,[20] which is in line with the results of the included studies in this study.[7,10,11,14,15]

Keystroke dynamics have important clinical implications. Firstly, unlike traditional neuropsychological assessments implemented in clinical settings that may not mirror a subject's real-life experience, keystroke dynamics can capturea more natural state,[22] implying high ecological validity. Secondly, the potential for long adherence allows continuous collection without additional effort, preventing missed detection of MCI and minimizing type I errors.[16] In contrast, periodic or occasional administration of neuropsychological assessments in clinical settings may lead to type I errors, missing critical timing for early intervention in patients with MCI.

Despite identifying the potential use of keystroke dynamics, this systematic has several limitations. Firstly, the number of the included studies was relatively small, making it challenging to generalize the findings of this study, but given the recent attention to keystroke dynamics in discriminating MCI, consistent results across the limited studies are noteworthy. Secondly, even though this study revealed that pause-related keystroke dynamics were commonly used, it was unable to determine which features were most useful for detecting MCI as discriminant power across keystroke dynamics was not compared. Finally, some of the included studies lacked statistical values, and methodological inconsistencies made presenting quantitative results through meta-analysis. These inconsistencies are notable, with variation in statistical approaches and data interpretation, contribute to the uncertainty of the current findings. To address this uncertainty, future research should strive for methodological consistency, employing ROC curve analysis with a diverse range of keystroke dynamics for a more robust understanding. Furthermore, comprehensive details in future studies would enhance overall understanding and reliability of reported differences in keystroke dynamics.

In conclusion, although the optimal feature of keystroke dynamics remains still unclear due to inconsistencies across the five studies, it was found that pause-related keystroke dynamics collected for at least 15 minutes show promise in distinguishing MCI. Despite current inconsistencies, these findings underscore the necessity for standardized methodologies in future research. If addressed, keystroke dynamics could become a valuable adjunct to conventional neuropsychological assessment, offering a non-invasive and potentially sensitive measure for MCI with an ecological validity and a long adherence.

Acknowledgement

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by Ministry of Education (No. 2021R1I1A3041487).

This work was supported by the Soonchunhyang University Research Fund.

Conflict of interest

The author declares that there is no conflict of interest.

Supplementary materials

Supplementary materials for this article can be found at http://www.sgecm.org.tw/ijge/journal/view.asp?id=29.

References

1. Petersen RC. Mild cognitive impairment as a diagnostic entity. *J Intern Med*. 2004;256:183–194. doi:10.1111/j.1365-2796.2004.01388.x
2. Park JH, Park JH. A systematic review of computerized cognitive function tests for the screening of mild cognitive impairment. *J Korean Soc Occup Ther*. 2016;24:19–31. doi:10.14519/jksot.2016.24.2.02
3. Park JH, Jung M, Kim J, Park HY, Kim JR, Park JH. Validity of a novel computerized screening test system for mild cognitive impairment. *Int Psychogeriatr*. 2018;30:1455–1463. doi:10.1017/S1041610218000923
4. Park JH. Machine-learning algorithms based on screening tests for mild cognitive impairment. *Am J Alzheimers Dis Other Demen*. 2020;35: 1533317520927163. doi:10.1177/1533317520927163
5. Rycroft SS, Quach LT, Ward RE, Pedersen MM, Grande L, Bean JF. The relationship between cognitive impairment and upper extremity function in older primary care patients. *J Gerontol A Biol Sci Med Sci*. 2019;74:568–574. doi:10.1093/gerona/gly246
6. Toosizadeh N, Ehsani H, Wendel C, Zamrini E, Connor KO, Mohler J. Screening older adults for amnestic mild cognitive impairment and early-stage Alzheimer's disease using upper-extremity dual-tasking. *Sci Rep*. 2019;9:10911. doi:10.1038/s41598-019-46925-y
7. Stringer G, Couth S, Brown LJE, et al. Can you detect early dementia from an email? A proof of principle study of daily computer use to detect cognitive and functional decline. *Int J Geriatr Psychiatry*. 2018;33:867–874. doi:10.1002/gps.4863

8. Buracchio T, Dodge HH, Howieson D, Wasserman D, Kaye J. The trajectory of gait speed preceding mild cognitive impairment. *Arch Neurol*. 2010; 67:980–986. doi:10.1001/archneurol.2010.159
9. Rabinowitz I, Lavner Y. Association between finger tapping, attention, memory, and cognitive diagnosis in elderly patients. *Percept Mot Skills*. 2014;119:259–278. doi:10.2466/10.22.PMS.119c12z3
10. Ntracha A, Iakovakis D, Hadjidimitriou S, Charisis VS, Tsolaki M, Hadjileontiadis LJ. Detection of mild cognitive impairment through natural language and touchscreen typing processing. *Front Digit Health*. 2020;2:567158. doi:10.3389/fdgth.2020.567158
11. Vizer LM, Sears A. Classifying text-based computer interactions for health monitoring. *IEEE Pervasive Comput*. 2015;14:64–71. doi:10.1109/mprv.2015.85
12. Iakovakis D, Hadjidimitriou S, Charisis V, Bostantzopoulou S, Katsarou Z, Hadjileontiadis LJ. Touchscreen typing-pattern analysis for detecting fine motor skills decline in early-stage Parkinson's disease. *Sci Rep*. 2018;8: 7663. doi:10.1038/s41598-018-25999-0
13. Bagias C, Sukumar N, Weldeselassie Y, Oyebode O, Saravanan P. Cord blood adipocytokines and body composition in early childhood: a systematic review and meta-analysis. *Int J Environ Res Public Health*. 2021; 18:1897. doi:10.3390/ijerph18041897
14. Van Waes L, Leijten M, Mariën P, Engelborghs S. Typing competencies in Alzheimer's disease: an exploration of copy tasks. *Comput Human Behav*. 2017;73:311–319. doi:10.1016/j.chb.2017.03.050
15. Stringer G, Couth S, Heuvelman H, et al. Assessment of non-directed computer-use behaviours in the home can indicate early cognitive impairment: A proof of principle longitudinal study. *Aging Ment Health*. 2023;27:193–202. doi:10.1080/13607863.2022.2036946
16. Chaibub Neto E, Bot BM, Perumal T, et al. Personalized hypothesis tests for detecting medication response in Parkinson disease patients using iPhone Sensor data. Pac *Symp Biocomput*. 2016;21:273–284.
17. Conijn R, Roeser J, van Zaanen M. Understanding the keystroke log: the effect of writing task on keystroke features. *Read Writ*. 2019;32:2353–2374. doi:10.1007/s11145-019-09953-8
18. Meulemans C, Leijten M, Van Waes L, Engelborghs S, De Maeyer S. Cognitive writing process characteristics in Alzheimer's disease. *Front Psychol*. 2022;13:872280. doi:10.3389/fpsyg.2022.872280
19. Saunders NL, Summers MJ. Attention and working memory deficits in mild cognitive impairment. *J Clin Exp Neuropsychol.* 2010;32:350–357. doi:10.1080/13803390903042379
20. Wu Q, Chan JS, Yan JH. Mild cognitive impairment affects motor control and skill learning. *Rev Neurosci*. 2016;27:197–217. doi:10.1515/revneuro-2015-0020
21. Aggarwal NT, Wilson RS, Beck TL, Bienias JL, Bennett DA. Motor dysfunction in mild cognitive impairment and the risk of incident Alzheimer's disease. *Arch Neurol*. 2006;63:1763–1769. doi:10.1001/archneur.63.12.1763
22. Iakovakis D, Hadjidimitriou S, Charisis V, et al. Motor impairment estimates via touchscreen typing dynamics toward Parkinson's disease detection from data harvested in-the-wild. *Front ICT*. 2018;5:28. doi:10.3389/fict.2018.00028