The Design of Cognitive Training Games for the Thai Elderly

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ABSTRACT

Cognitive aging is one of the main public health concerns, often involving a decline in memory and decision-making abilities as people age. Cognitive training games have been widely employed to improve working memory as well as enhancing short and long-term memory. In this study, we aim to develop a cognitive training game based on speech recognition technology under a Thai setting based user interface. The designed cognitive training tasks were conducted by performing electroencephalography (EEG) on six elderly volunteers, who passed the Thai mental state examination. The participants were instructed to memorize a series of pictures and calculate simple math questions. The EEG signals of the participants were recorded and analyzed during training. The participants engaged in four cognitive training tasks with three trials. An increase in training scores was found to be related to a rise in three EEG power spectrum bands: theta, alpha, and beta. Participants expressed the highest average level of satisfaction towards the easiest tasks in the four cognitive training games. This implies that when performing an easy task, an increase in the power spectral density of three EEG bands tends to evidently occur. As a result, the proposed cognitive training game could leverage the working memory of the Thai elderly. The game design can be enhanced by integrating human-based interactive tasks, such as handwriting and eye movements. Its replication on a larger scale should be assessed in the future work.

Keywords: Brain Training, Older Adults, Computer Game, Electroencephalography, Speech Recognition

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1. INTRODUCTION

Given the increase in senior populations and their rising life expectancy, there is a need to maintain quality of life by slowing the decline in age-related cognitive ability. This includes memory, decision-making, and cognitive control [1]. According to a survey conducted in 2017 by the Thai National Statistical Office [2], the number of elderly continues to grow rapidly with dementia being the main cause of decline in well-being. Moreover, the Ministry of Public Health, Thailand reported that approximately 600 000 older adults currently have Alzheimer's disease and this figure is predicted to rise to 1 117 000 by 2030 [2].

Memory is controlled by various cognitive processes which can be divided into two sub-systems: short-term memory (STM) and long-term memory (LTM) [3]. In previous studies [4–6], an episodic buffer model has been used to describe the mechanism of the working memory (WM), involving a short-term storage system and long-term memory. Working memory is dependent on the fronto-central regions of the brain, where the stimuli of the WM load corresponds to the EEG waves: theta, alpha, and beta. [7–8]. Khader *et al.* [7] found stronger alpha power for subsequent stimuli regarding a memory task over the occipital-to-parietal scalp sites. Furthermore, stronger theta power was found in such subsequent stimuli over the parietal-to-central region. These results support that the oscillation of alpha and theta waves imply LTM encoding [8]. Klimesch [9] also revealed that the theta and alpha frequency bands show correlation between short and long-term memory. However, Berger *et al.* [10] later reported that EEG alpha activity might not directly respond to semantic long-term memory access in a working memory task.

Various studies show that cognitive training games promote working memory [11–23]. Schweizer *et al.* [11] investigated whether brain training can improve cognitive function and the control of emotional material. The findings reveal that the intensive engagement of brain training can improve both the problem-solving ability and cognitive control processes in daily emotive environments. Nouchi *et al.* [12] investigated the effect of brain training games such as "Brain Age" and "Tetris" on cognitive function in the elderly. Participants in both the

Table 1: *Participant profiles and TMSE scores.*

Participant	Sex	Education	Age	TMSE
S-1	F	Grade 4	67	30
S-2	F	Grade 7	63	30
S-3	F	Grade 4	69	30
S-4	M	Grade 12	74	30
S-5	F	Grade 4	69	28
S-6	M	Bachelor's degree	72	29

Brain Age and the Tetris groups played the games for approximately 15 minutes per day, at least five days per week, over a four-week period. Each group played for a total of 20 days. The results reveal that playing the Brain Age game for four weeks could lead to improved cognitive ability in terms of executive functions and processing speed in the elderly volunteers. Shah *et al.* [13] demonstrated that a specific combination of physical and mental exercises for 16 weeks can improve verbal memory and increase the cerebral glucose metabolism in cognitively intact healthy older adults. Cognition was assessed using the Rey auditory verbal learning test, controlled oral word association test, and the CogState computerized battery at the baseline and eight and 16 weeks post intervention. Lu *et al.* [14] presented a cognitive training game design for the elderly. The systemic examination included the cognitive training structure, interface, interaction, instructions, and feedback, based on empirical evidence collected in natural settings. The results show that the developed cognitive training game was suitable for the participants, providing a high level of satisfaction. Kulason *et al.* [15] revealed the effect of simple calculation and reading aloud (SCRA) cognitive training in elderly Japanese postsurgical patients. This pilot study showed that the beneficial effects of SCRA interference on cognitive function and emotional state in postoperative elderly participants was not significantly noticeable, with a larger-scale examination recommended.

The cognitive fitness centre at the Chulalongkorn Memorial Hospital (incorporating the Thai Red Cross) provides a service to groups at risk of dementia by employing an electroencephalogram (EEG) to control a computer game. The game requires the participant to throw a ball into a hoop. However, this game has limitations when using it on the elderly.

As previously mentioned, cognitive training games such as Brain Age, Big Brain Academy, Brain Challenge, Tetris, and NeuroRacer are available commercially [11–37]. However, since these games are in English, they are not suitable for the Thai elderly. Although it is expected that the use of such brain training games can benefit cognitive functions, previous studies indicate that the impact may be limited for certain groups of participants. Therefore, in this study, a cognitive training game has been designed based on the Thai environment, involving foods, places, musical instruments, and utensils. Speech recognition technology has also been integrated into the design for the automatic examination of participants' answers. The hypothesis of this study is that the brain training game can be used to improve the working memory of the elderly.

2. MATERIAL AND METHODS

2.1 Participants

The data was recorded from six participants: four female and two male elderly volunteers aged between 63–74 years old (mean age = 69, SD age = 3.8), as presented in Table 1. They were all right-handed, healthy, and native Thai speakers. The study was conducted in accordance with the requirements of the Ethics Committee at Srinakharinwirot University, Thailand (reference code: SWUEC 252/2562E). The participants were fully informed of the research aim, study process, data recording, potential risk, and relevant compensation. All procedures were carried out with the written consent of the participants prior to the experiment. They had normal or corrected normal vision and reported no prior neurological conditions.

Participants were required to have a mini-mental health examination called the Thai mental state examination (TMSE). The TMSE is a quick screening test for assessing the cognitive function of the brain and widely used in dementia screening of the Thai elderly. The TMSE consists of a six-item questionnaire to measure orientation, registration, attention, calculation, language, and recall abilities. The TMSE is scored from 0 to 30 with lower scores indicating a greater degree of general cognitive dysfunction. A score of 23 suggests dementia. All volunteers passed the TMSE with an average score of 29.5 and an SD of 0.8 (Table 1).

2.2 Experimental Tasks and Trial Setup

Participants were seated about 60 cm from a 13-inch screen monitor with a total resolution of 1920 × 1080 pixels in a comfortable setting. The subjects participated in the experiment for three sessions. Each session lasted about 80 minutes: 15 minutes of preparation and installing the electrodes, 55 minutes of cognitive training, and 10 minutes of debriefing. In each session, the cognitive training game was divided into four tasks, each lasting about 12 to14 minutes with a 30-second break in between.

2.3 Cognitive Training Game Design

In this study, the cognitive training game was based on Thai cuisine, landmarks, musical instruments, and utensils. The game was implemented using 3.7 Python. The brain training game requires

(a)

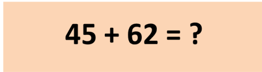
(b)

Fig. 1: *An example of task 1—memorizing pictures in order. (a) question, (b) answer choices.*

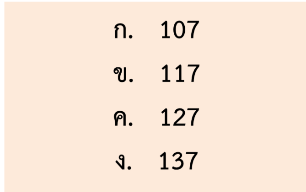
(a)

(b)

Fig. 2: *An example of task 2—identifying a missing picture. (a) question, (b) answer choices.*



(a)



(b)

Fig. 3: *An example of task 3—calculating basic arithmetic. (a) question, (b) answer choices.*

(a)

(b)

Fig. 4: *An example of task 4—identifying a missing picture (hard). (a) question, (b) answer choices.*

a speech recognition system operated under Google Cloud Speech API. In this study, the game was developed into four tasks containing 160 questions (40 questions for each task). Participants were asked to memorize a series of pictures and perform basic arithmetic calculations. The cognitive training game involved the cognitive operations of attention, executive function, memory, language, and visuospatial functions. Pictures were displayed for eight seconds and the choices displayed for seven seconds. Participants were asked to state one correct choice (kho kai, khor khai, khor khwai, or ngor ngoo) within seven seconds. Between questions, the investigator pressed the button to move to the next question. The four brain training tasks were explained in the order they were executed in the game:

Task 1: Memorizing pictures in order: the pictures are displayed for eight seconds. The task becomes more difficult as the number of pictures increases from 2, 3, 4, 5, and 6. (An example shows in Fig. 1)

Task 2: Identifying a missing picture: after displaying a series of pictures for eight seconds,

Fig. 5: *A subject performing the training game by memorizing pictures.*

one picture is removed, and the participant states which picture is missing within seven seconds. The subsequent questions become more difficult as the number of pictures increases from 2, 3, 4, 5, and 6. (An example shows in Fig. 2)

Task 3: Calculating basic arithmetic: addition, subtraction, multiplication, and division. Note that this task is set at the primary school level. (An example shows in Fig. 3)

Task 4: Identifying a missing picture (hard): this task is similar to task 2 but the pictures are placed in random positions. The subsequent questions become more difficult as the number of pictures increases from 2, 3, 4, 5, and 6. (An example shows in Fig. 4)

2.4 EEG Acquisition

EEG signals were recorded using a Neuroelectrics-Enobio® EEG system (NIC version 2.0.11.5) amplifier within the bandwidth of 1 and 40 Hz and a sampling rate of 500 Hz. The power line noise was filtered at 50 Hz. The EEG data was continuously recorded from 19 Ag/AgCl coated electrodes inserted into an electrode cap (easy-cap) according to the 10/20 international system. Recordings were made of 19 scalp locations: P7, P4, Cz, Pz, P3, P8, O1, O2, T8, F8, C4, F4, Fp2, Fz, C3, F3, Fp1, T7, and F7. Scalp electrodes were referenced using a dual electrode, connecting both CMS and DRL simultaneously to the same earlobe.

After each participant had closed their eyes and rested for a few minutes, they were asked to open them and memorize the pictures on the computer screen for eight seconds. The individuals were then asked to state one correct choice within seven seconds, as shown in Fig. 5.

2.5 EEG Analysis

The eight-minute signals for each cognitive training task were extracted. The Hamming window was applied to divide the signal into a window size of 120 seconds with an overlapping size of 60 seconds while EEGLAB [15] was used to analyze the EEG signals. EEGLAB (`http://www.sccn.ucsd.edu/eeglab/`) is a toolbox and graphic user interface running under the MATLAB environment. Welch's method was used to estimate the spectral density (PSD) of the four EEG rhythms: delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz). The PSD estimation based on Welch's method was applied to each window of the brain signals denoted by $x_m(n)$, which can be described as follows:

$$x_m(n) = \omega(n)\, x(n + mR) \quad (n = 0, 1, \ldots, M-1, \; m = 0, 1, \ldots, K-1) \tag{1}$$

where R is defined as a window hop size and K denotes the number of available frames. The periodogram and final PSD estimation of each brain wave of the m^{th} block are given by $P_{x_m,M}(\omega_k)$ and $\hat{S}_x^W(\omega_k)$ defined as

$$\begin{aligned} P_{x_m,M}(\omega_k) &= \frac{1}{M}\left|FFT_{N,k}(x_m)\right|^2 \\ &= \frac{1}{M}\left|\sum_{n=0}^{N-1} x_m(n) e^{-j2\pi nk/N}\right|^2 \end{aligned} \tag{2}$$

$$\hat{S}_x^W(\omega_k) = \frac{1}{K}\sum_{m=0}^{K-1} P_{x_m,M}(\omega_k) \tag{3}$$

After obtaining the PSD, the PSD of each EEG rhythm is the sum of PSD over the frequency range in each sub-band.

3. RESULTS AND DISCUSSION

After the individual had completed the TMSE task, the prototype of cognitive training game was presented. The six participants, S-1 to S-6, consisted of four females and two males, aged 63 to 74 years. All six participants completed the four training tasks before answering the questionnaire and expressing their general attitudes towards the game.

The overall scores in Table 2 increased from trials 1 to 3. The scores for task 1 from the three trials were highest, with those for task 4 being generally lower than the other cognitive training tasks (Fig. 6). The rate of change was higher for task 2 and lower for task 3. From the results, it can be observed that the more comprehensive and generic questions (task 1) yield a higher training score than the more difficult questions (tasks 2 and 4). The basic calculation in task 3 requires prior knowledge and therefore, the rate of change is slower than for the other tasks. Figs. 7 to 9 show an increase in theta, alpha, and beta over parietal-to-central electrodes in the subsequent training. These results support the concept that

Table 2: *Scores for the cognitive training game from trials 1, 2, and 3.*

Participant	Trial	Cognitive Training Task				Sum
		1	2	3	4	
S-1	1	23	8	12	22	65
	2	21	15	23	23	82
	3	28	21	26	25	100
	Mean	24.0	14.7	20.3	23.3	
	SD	3.6	6.5	7.4	1.5	
S-2	1	28	16	26	22	92
	2	36	24	29	25	114
	3	33	29	28	26	116
	Mean	32.3	23.0	27.7	24.3	
	SD	4.0	6.6	1.5	2.1	
S-3	1	19	7	7	9	42
	2	17	12	8	16	53
	3	31	20	16	14	81
	Mean	22.3	13.0	10.3	13.0	
	SD	7.6	6.6	4.9	3.6	
S-4	1	28	12	25	11	76
	2	26	16	27	10	79
	3	29	27	27	27	110
	Mean	27.7	18.3	26.3	16.0	
	SD	1.5	7.8	1.2	9.5	
S-5	1	8	18	29	11	66
	2	20	17	24	7	68
	3	13	24	30	21	88
	Mean	13.7	19.7	27.7	13.0	
	SD	6.0	3.8	3.2	7.2	
S-6	1	18	27	23	21	89
	2	23	25	30	21	99
	3	30	37	29	20	116
	Mean	23.7	29.7	27.3	20.7	
	SD	6.0	6.4	3.8	0.6	

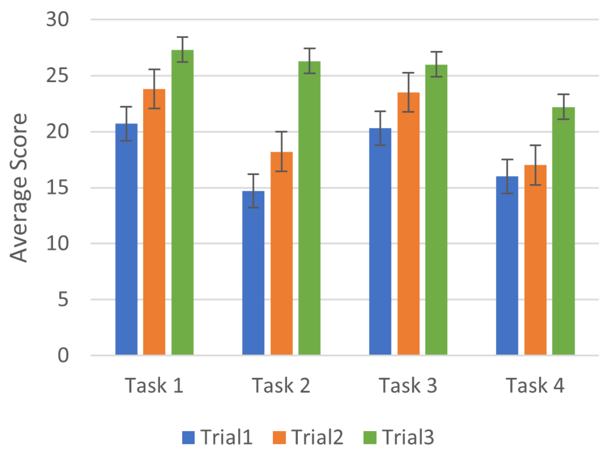


Fig. 6: *Average scores of the six participants for each task in three trials. The scores can be observed to increase from trials 1, 2, and 3, equating to 430, 495, and 611, respectively.*

oscillatory activities in the theta and alpha frequency range increase the WM load and modulate successful LTM encoding [7–9].

Table 3: *Comparison of the training scores and power spectral density obtained from the training in trials 1, 2, and 3.*

Hypothesis	p-value			
	Training Score	Theta	Alpha	Beta
$H_0 : \mu_{T1} = \mu_{T2}$	0.0190	0.8084	0.0271	0.0046
$H_0 : \mu_{T1} = \mu_{T3}$	0.0001	0.0435	0.0028	0.0015
$H_0 : \mu_{T2} = \mu_{T3}$	0.0056	0.0905	0.1171	0.2443

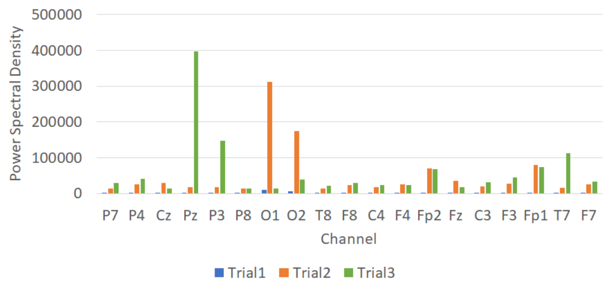


Fig. 7: *Power spectral density comparing the EEG theta band from trials 1, 2, and 3 from participant S-2.*

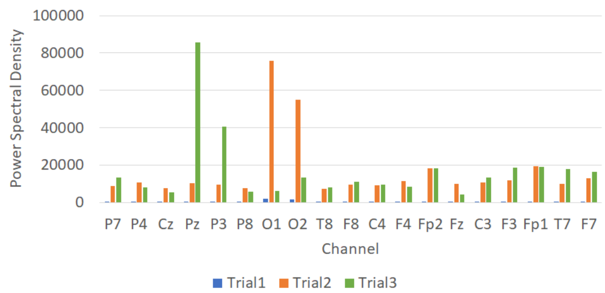


Fig. 8: *Power spectral density comparing the EEG alpha band from trials 1, 2, and 3 for participant S-2.*

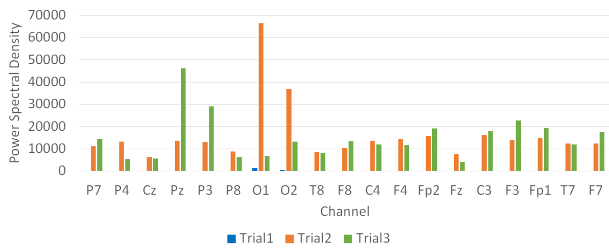


Fig. 9: *Power spectral density comparing the EEG beta band from trials 1, 2, and 3 for participant S-2.*

In Table 3, the hypotheses were set to examine the mean of (i) the training scores, (ii) the PSD of theta, (iii) alpha, and (iv) beta waves. The results indicated that the training scores between trials 1 and 2 show significant difference as well as the PSD of alpha and beta from such compared trials. A comparison of the metrics between trials 1 and 3, shows significant

Table 4: *Relative PSD in theta, alpha, and beta bands obtained from trials T1, T2, and T3 for participant S-1.*

Task	Theta			Alpha			Beta		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
1	1.00	1.00	0.24	1.00	1.00	0.13	1.00	1.00	0.15
2	0.70	0.22	0.93	0.58	0.30	0.70	0.70	0.48	0.66
3	0.77	0.41	0.08	0.59	0.48	0.06	0.68	0.65	0.08
4	0.72	0.33	1.00	0.51	0.50	1.00	0.67	0.77	1.00

Table 5: *Relative PSD in theta, alpha, and beta bands obtained from trials T1, T2, and T3 for participant S-2.*

Task	Theta			Alpha			Beta		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	0.72	0.43	0.33	0.79	0.51	0.31	0.85	0.59	0.29
3	0.54	0.70	0.64	0.43	0.85	0.47	0.51	0.88	0.46
4	0.56	0.38	0.18	0.43	0.48	0.18	0.52	0.57	0.26

Table 6: *Relative PSD in theta, alpha, and beta bands obtained from trials T1, T2, and T3 for participant S-4.*

Task	Theta			Alpha			Beta		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
1	0.47	1.00	1.00	0.69	1.00	0.85	0.74	1.00	0.76
2	0.31	0.41	0.74	0.80	0.51	1.00	1.00	0.66	1.00
3	0.28	0.52	0.56	0.68	0.61	0.60	0.87	0.72	0.53
4	1.00	0.79	0.84	1.00	0.75	0.95	0.99	0.79	0.85

Table 7: *Relative PSD in theta, alpha, and beta bands obtained from trials T1, T2, and T3 for participant S-6.*

Task	Theta			Alpha			Beta		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
1	0.45	0.11	1.00	0.39	0.06	1.00	0.74	0.05	1.00
2	0.16	0.18	0.71	0.13	0.08	0.20	0.49	0.06	0.37
3	0.40	0.32	0.96	0.28	0.12	0.26	0.59	0.12	0.26
4	1.00	1.00	0.78	1.00	1.00	0.19	1.00	1.00	0.21

differences. Lastly, a comparison of the four metrics between trials 2 and 3 revealed that only the training score was significantly different.

The PSD of brain rhythms in each trial was also normalized by a specific maximum power as presented in Tables 4 to 7. Task 1 yields a higher power spectral density in theta, alpha, and beta frequency bands than the other tasks, which corresponds to a higher score for task 1. The harder or more complex games yielded lower PSD and training scores. This implies that the comprehensive training task potentially provides a better improvement in the working memory of the elderly than the more difficult

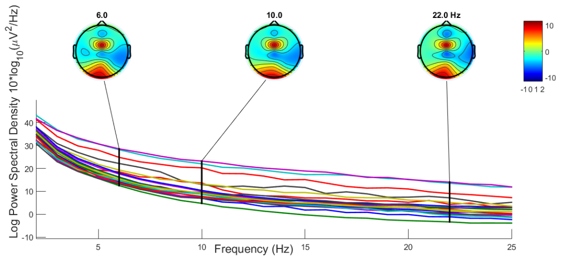


Fig. 10: *An example of the spectra and map in the first trial.*

training questions. However, the higher theta, alpha, and beta of task 1 could be due to the high level of attention and concentration exhibited by participants at the beginning of the session.

The results in Tables 4 to 7 support the assumption from a previous study [16] that the amplitude of the alpha rhythm tends to decrease as tasks become more difficult or involve mental arithmetic. Tasks 2 and 4 contain more difficult questions, while task 3 requires arithmetic calculation. The alpha rhythms of tasks 2, 3, and 4 are apparently more inferior than those of the easier questions in task 1.

Fig. 10 shows the spectra of EEG rhythms obtained from the 10/20 system. The working memory load was observed by an increase in PSD from frontal to occipital regions. This shows that the training tasks stimulate this area of the brain, especially the visuospatial working memory activated by memorizing the objects appearing on the screen.

The errors occurring when playing the game are not only due to incorrect answers being provided but also the mistranslation from speech to text (translated by Google Cloud Speech API). In some cases, participants selected the appropriate choices, but the system wrongly translated the words. For example, “kor kai” was recognized as “kra-tai” and “kao lao”; “khor khai” was recognized as “kong krai” and “pror krai”; “khor khwai” was recognized as “call line” and “kao kwaai”; while “ngor ngoo” was recognized as “waa ngai” and “ao ngoo”.

It is important that the experiment should be conducted in a suitable environment such as low noise and sufficient light. Speech recognition may not be entirely suitable for this training, although the cognitive training score still reflects an increase in WM load.

After completing the cognitive training tasks, the participants were asked to rank their level of satisfaction towards the four cognitive training tasks. On average, the highest score was found on the performance of task 1, while the lowest score was found on that of task 4, as shown in Table 8 and Fig. 11.

The scores obtained from the cognitive training game, power spectral density, and satisfaction show

Table 8: *Satisfaction scores of game participants.*

Participant	Satisfaction			
	Task 1	Task 2	Task 3	Task 4
S-1	4	1	3	2
S-2	4	2	3	1
S-3	4	2	3	1
S-4	4	3	1	2
S-5	2	3	4	1
S-6	3	4	2	1
Total	21	15	16	8
Mean	3.50	2.50	2.67	1.33
SD	0.84	1.05	1.03	0.52

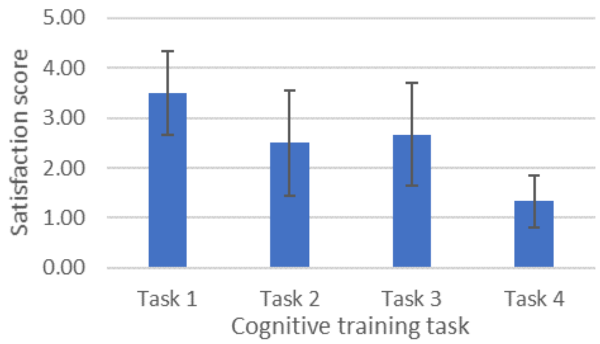


Fig. 11: *Average and standard deviation of satisfaction scores for the four cognitive training tasks.*

corresponding trends, providing evidence to support that task 1 of the cognitive training promotes working memory more effectively than that from the other tasks. This implies that the comprehensive and straightforward training game could enhance the working memory of the elderly participants. In future work, we plan to create a more attractive cognitive training game by adding emotional scenarios, such as fun, relaxed or stressful tasks to the game presentation rather than merely tension. In addition, the integration of human-based interactive responses, such as handwriting and eye movements should be investigated.

4. CONCLUSION

In this study, we have proposed a cognitive training game for the Thai elderly, integrated into the Thai environment with a use of speech recognition. The training game consists of four training tasks, mainly categorized as memorizing a series of pictures and calculating basic arithmetic. Our findings suggest that the elderly could benefit from the training, with improvements being observed in four metrics: (i) the training scores and (ii)–(iv) the power spectral density of the three brain rhythms: theta, alpha, and beta. The motivation and concentration of the elderly participants were measured through these four metrics and greatly depend on the nature of the training task. The questions could be more comprehensive and simpler. The answers obtained from the speech recognition revealed several errors caused by human errors and computer glitches. It is suggested that the Thai elderly volunteers should be asked to memorize pictures showing familiar objects or places. Consequently, in the future, it would be beneficial to create more attractive games using emotional materials integrated with handwriting and eye-tracking interactions. This will be conveyed to enhance working memory for Thai elderly effectively.

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