Using an ANN-based computational model to simulate and evaluate Chinese students' individualized cognitive abilities important in their English acquisition

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Abstract- From a psycholinguistic perspective of view, there are many cognitive differences that matter to individuals' second language acquisition (SLA). Although many computer-assisted tools have been developed to capture and narrow the differences among learners, the use of these strategies may be highly risky because changing the environments or the participants may lead to failure. In this paper, we propose an artificial neural network (ANN) based computational model to simulate the environment to which students are exposed. The ANN computational model equips English teachers with the ability to quickly find the predicting factors to learners' overall English competences and also provides teachers with the ability to find abnormal students, based on reviewing their individualized ANN trajectories. Finally, by observing the compound effects of cognitive factors using the same evaluation scale, new hypotheses about the mutual relationships among the phonological awareness, phonological short-term memory and long-term memory abilities of their students can be generated. Our experimental ANNs suggested three detailed corresponding conclusions for the participants' English teachers. These results provide teachers with guidance in designing and applying cognitive ability-related intervention strategies in their L2 pedagogical activities.

Key words- cognitive ability, short-term memory, long-term memory, phonological awareness, artificial neural network, computational model

1. Introduction

Individual factors that influence language learning include many cognitive individual differences (Gardner, 1985), such as the cognitive abilities related to understanding, perception, concentration, attention and memory (Chrysafiadi & Virvou, 2013; Yang et al., 2014). Methods addressing the cognitive individual differences in second language acquisition (SLA) are called psycholinguistic approaches (Thorne & Smith, 2011); improving students' related learning skills in SLA by generating compensation strategies for the corresponding cognitive ability has long been believed to be one of the most effective methods. Among these cognitive factors, working memory capacity is an important cognitive-related predictor of success in second-language learning (L2) (Sawyer & Ranta, 2001), and many related studies have testified to its importance in English (L2) learning (Kormos & Safar, 2008; Papagno & Vallar, 1995; Service & Kohonen, 1995; Speciale & Ellis, 2004). Another important cognitive-related factor that influences English learning is phonological awareness (Comeau et al., 1999; Cunningham, 1990; Gottardo et al., 2016; Ho & Bryant, 1997; Huang & Hanley, 1997). Wagner and Torgesen (1987) concluded that phonological awareness and short-term verbal memory can be regarded as the two primary phonological processing skills of SLA.

The conclusions made by psycholinguistic studies provide the theoretical basis for the practising of 'behavioural interventions' for students to eliminate the cognitive individual differences in SLA. To narrow students' differences in short-term memory ability, Chun and Payne (2004) investigated the relationship between learners' phonological working memory capacity and their looking up behaviours for the words displayed on a screen. The results showed that students with lower phonological working memory capacity will generate a compensation while they look up the words displayed on a screen. Chen et al. (2008) also concluded that providing students with appropriate interventions could generate compensations for their shortages in phonological short-term memory ability. In their experiment, they provided students (with lower phonological short-term memories and higher visual short-term memory ability) with adapted learning contents, which allow the students to benefit greatly from the pictorial annotations.

In addition to the studies focusing on the interventions associated with short-term memory ability, other studies have focused on the interventions targeting phonological awareness. Lambacher (1999) developed sound recording software to capture and discover different pronunciation patterns produced by Japanese students. The experiment showed that discovering Japanese students' pronunciation patterns and comparing those patterns with native English speakers' patterns can rectify their inherent phonological awareness habits related to some specific phonemes that might be influenced by the mother language. Liakin et al. (2015) investigated the effectiveness of the acquisition of the French vowel /y/ in a mobile-assisted learning environment. Their research suggested that with an instant visual feedback provided by the mobile application, students' phonological awareness for the French vowel /y/ significantly improved compared to the students who went through a traditional classroom learning process. Quintana-Lara (2014) used Acoustic Spectrographic Instructions in the learning of the English vowels /i/ and / I / in Spanish students, their experiment showed that Acoustic Spectrographic Instruction significantly improved the pronunciation of both vowels. The results lend support to the use of acoustic features of speech and spectrography as an effective intervention method to solve the problems caused by lower phonological awareness ability.

In addition to the aforementioned intervention strategies focusing on short-term memory ability and phonological awareness ability, other cognitive abilities are also being considered in the development of new technologies. Roussel (2011) used screen monitoring tool to record students' mouse movements while they listened to L2 MP3 files. They found a relationship between the number of movements and comprehension, and based on this finding, they designed several types of cognitive strategies for the participants and concluded that metacognitive strategies are a useful resource to compensate comprehension shortages, although it may increase cognitive load. Tickler and Shi (2017) used eye trackers to discover participants' attention patterns when they were using online Chinese tutoring software. They found that social contents displayed on the screen attracted 20% fixation, which led to a new hypothesis for improving students' attention performance by enhancing the quality of the computer-human interfaces. Boers et al. (2017) argued that the amount of attention given to words is a significant predictor of their retention in memory. They used eye tracking technology to support this hypothesis and concluded that increasing students' attention for important words is useful in word acquisition. Another use of eye tracking technology in behavioural intervention is to monitor and evaluate its effectiveness in concentration controlling (Liu, 2014); Liu's study suggested that using morphological instructions in student vocabulary learning can effectively increase students' fixation times in vocabulary and morpheme areas.

The aforementioned behavioural interventions have received great attention, however, transferring the use of these strategies may still be highly risky because changing the environments or the participants may cause failure. For example, although many previous studies have proven a strong correlation between phonological short-term memory and different English language competencies, there still remains some contradictory results. Kormos and Safar (2008) suggested that phonological short-term memory plays no role in the achievement related to L2 because the participants who memorized the phonological words also used other cognitive abilities. It is difficult to evaluate which result is more accurate, however, note that the participants in the related studies were exposed to different environment configurations (e.g., the different richness of the linguistic environment to which the students were exposed).

Therefore, to improve the precision of the effectiveness of the cognitive abilities on L2, a model should be built to simulate the environmental configurations that students were exposed to and then to evaluate to what degree those cognitive abilities can affect L2 learning in such an environment before designing and conducting interventions related to cognitive ability. However, the lack of professional techniques will prevent L2 teachers from implementing this work; in addition, the time and energy being consumed in data processing and analysis is also significant. Thus, we would further argue that it is necessary to build a computer-based tool to help L2 teachers construct a cognitive ability evaluation model for their students.

Based on this research background, a computational model can provide a feasible solution because it reveals not only the common features shared by the individuals within a same class but also simulates the minor differences between individuals. A primary reason to use computational models in cognitive-related research is to understand human learning processes (Mareschal & Thomas, 2007; Yang, Thomas, & Liu, 2017), and the computational models of development, particularly those employing artificial neural networks (ANNs), have provided hypotheses about the mechanistic bases of language development (Christiansen & Chater, 2001) and language deficits (Mareschal & Thomas, 2007). As opposed to classical generative approaches (Chomsky, 1986, 2014), which characterize language in terms of a domain-specific form of knowledge representation called grammar (Joanisse & Seidenberg, 1999), connectionist computational models try to transfer human learning behaviours into mapping problems that regard grammar as being characteristic of some aspects of the behaviour (D. E. Rumelhart & Mcclelland, 1986; Seidenberg & McClelland, 1989). For example, a population of 1000 ANNs was exposed to the language domain (English past tense), and their developmental trajectories were used to simulate different children's vocabulary acquisition processes. The amount of information available in the input was analogous to the richness of the linguistic environment a child was exposed to, and the variations in the parameters could be thought of as simulating the different learning capabilities of children (M. S. Thomas & Knowland, 2014). Building up the correlations between input and output based on the experience (training data) in a black-box way is the basic working mechanism of a connectionist computational model. In addition, a number of schools have integrated connectionist computational thinking into their language teaching to help their students cognize language in a different manner (Hulstijn, 2003).

2. Purpose and research questions

The first purpose of our study is to provide English (L2) teachers with a convenient method to help them quickly build a cognitive ability evaluation model for their students, with the help of a computer-based tool to check which cognitive ability can be used as a predictor of their English learning competence. The second purpose is to provide English teachers with a general measuring scale for understanding and observing the compound effects that the important cognitive abilities (phonological awareness ability, phonological short-term memory and long-term memory) may produce on their students' English learning. These two purposes could be further used to guide English teachers to make reasonable hypotheses and designs for the cognitive interventions they are intending to use for their students. The final purpose of our study is to verify the validity and reliability of this computational model-based tool in simulating typical students' characteristics related to different cognitive abilities and in predicting their future performances.

Based on the purposes listed above, we sought to investigate the following two specific questions:

1. Are phonological awareness ability and phonological short-term memory ability more important to the participants in their English learning than the long-term memory ability?
2. What are the compound effects of the phonological awareness ability, the phonological short-term memory and the long-term memory ability on participants' English learning?

3. Methodology

3.1 Participants

Fifteen students were selected from over 200 grade-one students at Zongbei Experimental Middle School, Chengdu, Sichuan. The participants included 9 girls and 6 boys (ages 12–13 years, mean=12.33, sd=0.271), all of whom had not yet learned the rules of generating past tenses from verbs but were ready to learn. In addition, all participants performed in the normal range on their first language. The experiment was conducted in the middle of their first semester of the first year; the students were ranked on different courses by the school according to their entrance examination scores and their regular test scores (including unit test scores and monthly test scores). Students in the top 10% were labelled as excellent, those in the bottom 10% were labelled as extremely poor, while the remaining were clustered in the normal group; the participating students in our experiment were randomly chosen from each group.

Five students were evaluated as having a learning disorder, with their overall English competencies being extremely poor (labelled as individuals 02, 04, 05, 11 and 12). Five were evaluated as normal students (labelled as individuals 01, 08, 09, 10 and 15), and the remaining 5 were evaluated as excellent students (labelled as individuals 03, 06, 07, 13 and 14). In addition to the true participants, there was a virtual student with the best convergent learning trajectory who was considered as the baseline to provide a benchmark scale for all participants to compare and simulate their individualized cognitive abilities. The baseline labelled 'Base_line' in Figures 3-5 is a learning line that represents the current environmental configuration.

3.2 Materials

Learning the past tense of verbs was a commonly used base model for computational models to provide hypotheses of language-related cognitive processes (Yang & Thomas, 2015). For a long time, verbs and their corresponding past tenses have been regarded as a paradigmatic linguistic subsystem exhibiting the fundamental properties of language (Joanisse & Seidenberg, 1999). In this paper, Plunkett and Marchman's 19 binary phonological-featured coding mechanism (Plunkett & Marchman, 1993) is chosen to represent the verbs and their past tenses. Verbs being used in the experiments are three-phoneme ones with which each phoneme is encoded in 19 binary bits. The corresponding meaning of those 19 binary phonological features can be described as follows: sonorant, consonantal, continuant, voiced, labial, anterior, +coronal, back, strident, nasal, lateral, -coronal, high, central, low, rounded, tense, and diphthong. However, Plunkett and Marchman's original phonological coding mechanism cannot cover all the phonemes appearing in the three-phoneme verbs. Six extra phonemes are added in our experiment. In addition, a 'Null' coding is added to cope with a specific situation. The newly added phonemes are /ə:/, /iə/, /tr/, /ts/, /dr/ and /dz/, and the complete coding mechanism of the phonemes is listed in Appendix A.

The suffix of the past tense is encoded in 5 bits for the different types of past tense: regular, identical irregular, vowel change irregular and arbitrary irregular. X, W, Y and Z are labels used to represent the aforementioned different kinds of suffixes, where X refers to [d], Y refers to [t], Z refers to [ed], and W represents [none]. Their coding details are provided at the bottom of Appendix A. Each dataset used in this paper comprised 50 real verbs, listed in Table 1, and their coding details could be found in Appendix A. The verbs were selected from the students' English book and they were part of the middle school final examination syllabus. The composition of the word sets complied with the data structures that were previously used in the ANN computational simulations (M. S. C. Thomas et al., 2010; Yang & Thomas, 2015; Yang et al., 2017): 80% were regular verbs, 20% were irregular words; 10% of the irregular verbs were arbitrary, 20% of the irregular verbs were identical, and 70% of the irregular verbs were vowel changed. The correct mappings from verbs to their past tenses are considered as training data sets, which are used to simulate a student's virtual learning process. The real mappings of the individuals are used as testing data sets to evaluate their performance differences based on the same benchmark (virtual) learning trajectory which is simulated by a trained artificial neural network.

No.	Task1	Task2 and 3	No.	Task1	Task2 and 3	No.	Task1	Task2 and 3
1	allow	roll	18	live	use	35	cook	hike
2	annoy	run	19	lock	wait	36	cough	hope
3	appear	dress	20	hang	wake	37	peel	join
4	ask	drive	21	love	walk	38	cry	kill
5	bake	drop	22	meet	wash	39	play	kiss
6	bark	face	23	miss	watch	40	pull	knock
7	burn	fail	24	need	wave	41	push	laugh
8	call	fall	25	offer	look	42	race	learn
9	can	boil	26	sing	wipe	43	rain	treat
10	obey	fell	27	order	work	44	ring	turn
11	cause	fill	28	pack	write	45	rush	bide
12	chase	fit	29	park	stay	46	sail	feed
13	chat	take	30	pass	store	47	put	grow
14	light	heat	31	glue	suit	48	ride	crow
15	pierce	kid	32	pick	surf	49	get	cut
16	let	fool	33	chop	talk	50	raise	read
17	like	type	34	come	guide			

Table 1. Verbs used in the experiment

3.3 Instrument

Artificial neural network (ANN) is a computational model of which simulates the process of information passing among neurons. If the connections between neurons form no cycle, the network is referred to the feedforward network. A feedforward ANN is composed of 1) an input layer, 2) one or multiple hidden layers, and 3) an output layer. Neurons on the input layer represent the features that collected from the sample data, and neurons on the output layer represent the expected outcomes, and the fully-connected connections only exist among neurons belonging to different layers (as illustrated in Figure 2). The applications of the ANN-based computational model in both L1 and L2 acquisition can be classified into two major categories: predicting language learning performance (Slavuj, Meštrović, & Kovačić, 2016; Wang & Liao, 2011) and solving mapping problems (Kjellström & Engwall, 2009; M. S. C. Thomas et al., 2010). In the first situation, ANNs are considered as a classifier, while in the second situation, ANNs work as regressors, for example, building a non-linear regression model to map acoustic features to articulatory features (acoustic-to-articulatory inversion process) with audiovisual features on the input layer and articulatory parameters on the output layer (Kjellström & Engwall, 2009).

Besides its regressor role in acoustic-to-articulatory inversion simulation regarding L2, ANN has also been used as a regressor to simulate the mapping processes in L1 acquisition to help understanding the language developmental processes of the English native speakers (M. S. C. Thomas et al., 2010). For example, by reducing the learning rate of an ANN, it can simulate a child's language acquisition delay and by decreasing the number of the neurons on the hidden layer, it can simulate a defect language environment to which an individual is exposed. It can also simulate an intervention process by adding extra training data to an ANN, and observing the possible outcomes based on the simulation results before clinically using those intervention strategies (Yang & Thomas, 2015).

Although ANN computational model can be used in language acquisition, its main contribution relies on its powerful simulation ability and its assistance to reveal the truths that are not easily being found by pure data observation or by statistical data analysis. In our work, the three layer Back Propagation ANN (D. Rumelhart & Mcclelland, 1988) is adopted as a regressor to simulate the Chinese students' mapping process from the three-phoneme English verbs to the corresponding past tenses. It is a feedforward neural network with logistic sigmoidal functions as the activation function for the hidden layer and the output layer, and the weights are optimized through back propagation algorithm.

3.4 Procedure

The general procedure of the experiment involved the following six steps:

(1) First, test that could be executed both by the computational model and by the participant students were designed. The test includes 3 cognitive-related tasks: phonological awareness-related task (task 1), verbal short-term memory ability-related task (task 2) and verbal long-term memory ability-related task (task 3).

(2) Participants were required to implement the tasks; their performance in each task were recorded and encoded.

(3) The ANNs related to different cognitive abilities were trained with the respective training datasets.

(4) The encoded performances of the students were inputted into the trained ANNs to obtain the outputs.

(5) The participants' learning RMSE (root mean squared error) lines produced by the ANNs were observed, which represented their current and predicted future performances on the cognitive-related

tasks.

(6) Finally, meaningful results related to the cognitive abilities were observed and generated; these findings are crucial for EFL students' second language learning, and could help teachers gain more insights into their students' learning status.

Details regarding each step are described in the following subsections.

3.4.1 Conducting the three cognitive ability-related tasks

To evaluate the cognitive-related differences using the same evaluation scale, the verbs and past tenses involved in all 3 tasks follow the same encoding plan, and 50 three-phoneme verbs and their past tenses compose a data set for each task. The details of the three tasks are described as follows:

(1) Phonological awareness-related task (Task 1)

The phonological awareness-related task is designed to reflect the basic phonological awareness ability for English (L2) of the students whose native language's (Chinese) phonological feature space is different from English. This task collects the students' basic phonological awareness performance for English which can reflect individuals' different phonological sensitivity since each phoneme of the verbs and past tenses is encoded in 19 phonological features. In this task, the teacher only taught students the new phonemes' pronunciation instead of teaching them the past tense's construction rules. For example, before presenting to the students the past tenses that have the 'ed' suffix, the pronunciation '/id/' will first be taught. If the past tense of the given verb is arbitrary or vowel-changed, new phonemes appearing in the past tense will be primarily taught by the teacher. The verbs used in this task can be found in Table 1 and their pronunciations can be found in Appendix B. Four steps are involved to implement this task:

a. The English teacher helps the participant students to correctly pronounce the given 8 verbs (last time is 10 verbs).

b. The English teacher teaches the participant students the new pronunciations that will appear in the past tenses of the verbs mentioned in step a.

c. The participant students are required to pronounce the past tenses of the verbs.

d. Each participant student's pronunciation of each verb's past tense is recorded.

(2) Short-term memory ability-related task (Task 2)

This task is mainly used to evaluate participant students' short-memory ability related to English pronunciation, it tests students' phonological repetition ability towards regular and irregular changed past tenses, and is a transformation of the classical word-span test. Fifty 3-phoneme verbs will compose the data set (seeing Appendix A and C for their coding details). To implement this task, three steps are involved:

a. The English teacher helps participant students to correctly pronounce the given 8 verbs (last time is 10 verbs) and their past tenses.

b. Participant students are presented with 8 verbs (last time is 10 verbs) at a time, requiring them to pronounce their past tenses.

c. Each participant student's pronunciation of each verb's past tense is recorded.

(3) Long-term memory ability-related task (Task 3)

The long-term memory ability-related task is used to evaluate participant students' long-memory ability with regard to English pronunciation and will be implemented based on the short-term memory ability-related task. Moreover, it will share the same data set with the short-term memory ability-related task. The data set used in this task, however, will have a one-week delay compared with the data sets used in the short-term memory ability-related task. Like Task 2, the past tenses of the verbs not only include regular changings but also some irregular ones. So that the results of the experiment would not be interfered by the mapping rules. This task is implemented in two steps:
a. The verbs used in last week's short-term memory ability-related task are presented to the participant students, requiring them to pronounce those verbs' past tenses.
b. Each participant student's pronunciation of each verb's past tense is recorded.

The three tasks are repeatedly executed for 7 weeks, and the specific implementing of the 3 tasks scattered on the timeline is illustrated in Figure 1. Every time, each task takes approximately 5-10 minutes for each participant to complement the test. To remain consistent with the restraints requested for testing short-memory ability, each time only 8 verbs and their past tenses are involved (the last time involves 10 verbs).

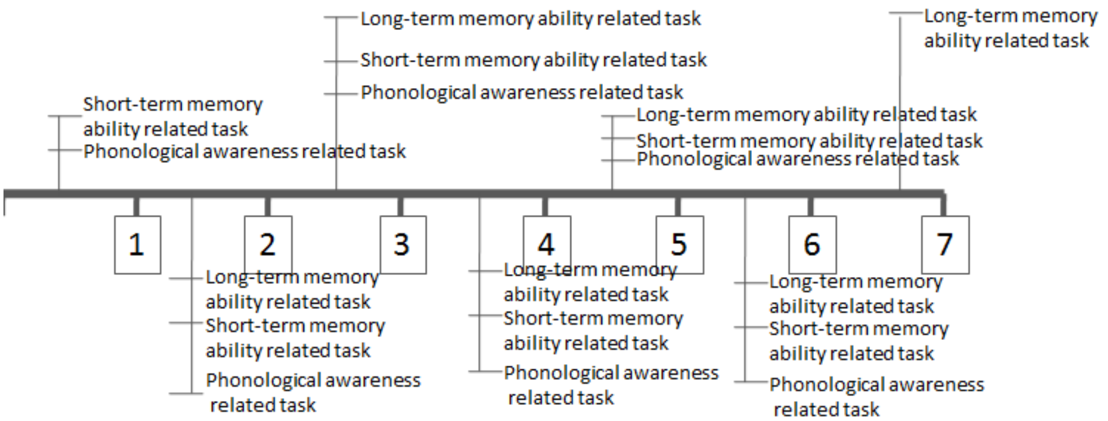

Figure 1. Three tasks' executive timeline

3.4.2 Building up a computational model based on three artificial neural networks

As illustrated in Figure 3, three artificial neural networks (ANNs) will be constructed to simulate the current learning environment. These three ANNs will be further used as a platform to evaluate the different students' learning performances for three kinds of cognitive abilities. The training data set for each ANN comprises 50 three-phoneme verbs and their past tenses.

The ANN used to simulate the process of task 1 is a 62*40*62 three-layered one, which has 62 neurons on the visible layer, 40 neurons on the hidden layer and 62 neurons on the output layer. Both the input and the output of this ANN are three-phoneme past tenses. ANNs used to simulate the process of tasks 2 and 3 are in the form of 57*30*62, where numbers 57, 30 and 62 correspond to 57 neurons on the visible layer, 30 neurons on the hidden layer and 62 neurons on the output layer. The input of those two ANNs are three-phoneme verbs and the output are their past tenses.

We use 100 epochs to simulate each week, and the training data sets at the beginning of each 100*i+1'th (where $i \in [0,5]$) epoch are the pre-defined 8 (the last time is 10) verbs and their past tenses.

After successfully training the ANNs, student participants' actual performances on those tasks will be input into the ANNs as testing data sets to evaluate the simulation abilities of the ANN-based computational model.

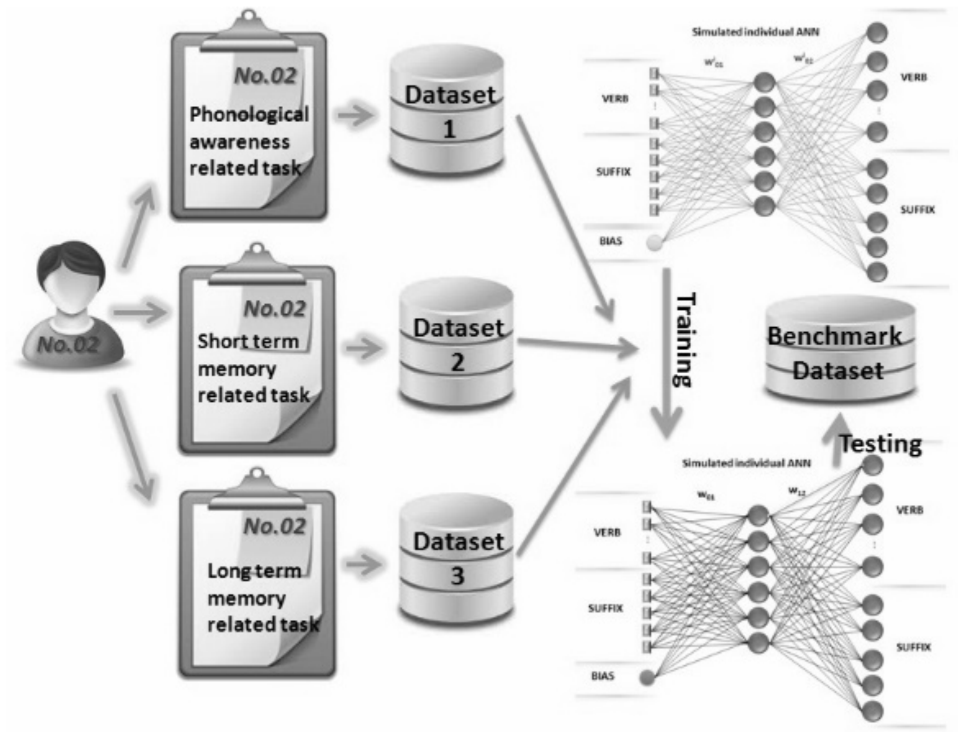

Figure 2. A sample student (No.02) is evaluated by 3 trained artificial neural networks

3.4.3 Generating and collecting data from the ANNs

In Figures 3–5, the participant student i's performance of each task at each learning epoch m is computed through the following formula, which is a relative learning performance compared with a virtual learner who is allowed to make mistakes during his/her learning process. In formula (1), S_i refers to the student i's pronunciation of the verbs and their past tenses, and SV refers to the training data set (verbs and the corresponding past tenses used in the experiment). $|S_i|$ refers to the number of patterns that the ANN is processing at that epoch. $Net_3^m(.)$ is the sigmoid output of the final layer of an ANN at epoch m, and w_j^m refers to the weight matrix of the ANN on layer j at epoch m based on the training data set SV. $|S_i| = |SV|$ is different at different learning phases, and $|S_i| = 8 * (\left\lfloor \frac{m}{100} \right\rfloor + 1)$, if $m \in [1,500)$; otherwise, $|S_i| = 50$).

$$RMSE_i^m = \frac{1}{|S_i|}\sqrt{\sum \|Net_3^m(S_i) - Net_3^m(SV)\|^2} \quad (1)$$

$$Net_j^m(Data) = \begin{cases} sigm(Data, w_1^m), & j = 1 \\ sigm\left(Net_{j-1}^m, w_j^m\right), & j > 1 \end{cases} \quad (2)$$

According to formulas (1) and (2), the output of the ANNs regarding each individual is the standard deviation of the benchmark line.

4. Results of the experiment and the related data analysis

4.1 Evaluating the effectiveness of 3 kinds of cognitive abilities on students' English learning

Figures 3 to 5 are the participant students' current and expected future performances with regard to phonological awareness-related tasks, short-term memory ability-related tasks and long-term memory ability-related tasks, respectively. The first 500 epochs simulate the experimental process of the students, while the last 400 epochs simulate their potential performances. From the three charts, it is clear that almost all testing students' basic phonological awareness ability will be convergent, while their short-term memory-related ability and their long-term memory ability will diverge in the future.

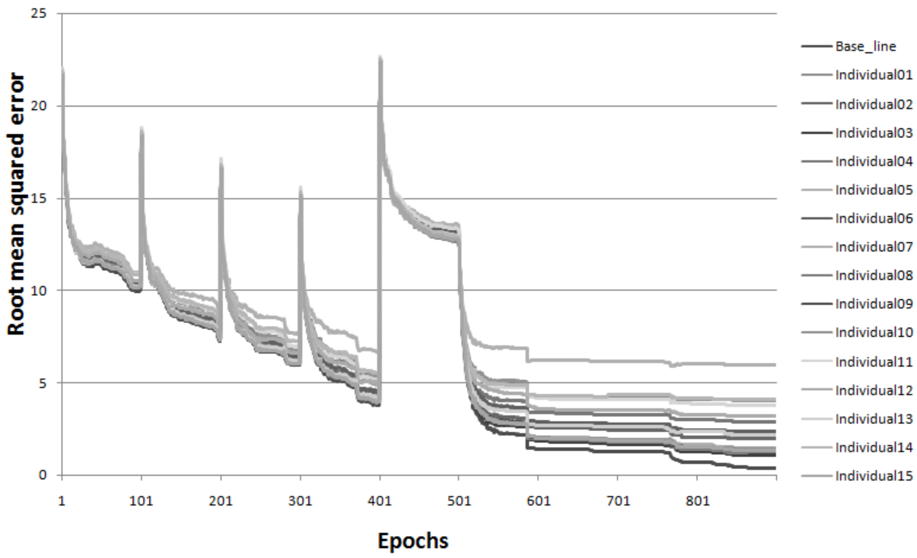

Figure 3. Individualized performance on Task 1

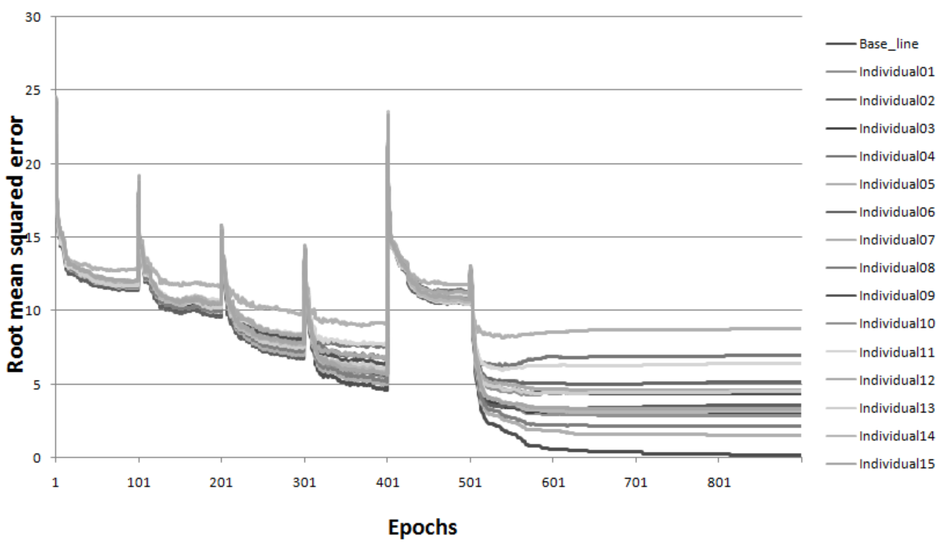

Figure 4. Individualized performance on Task 2

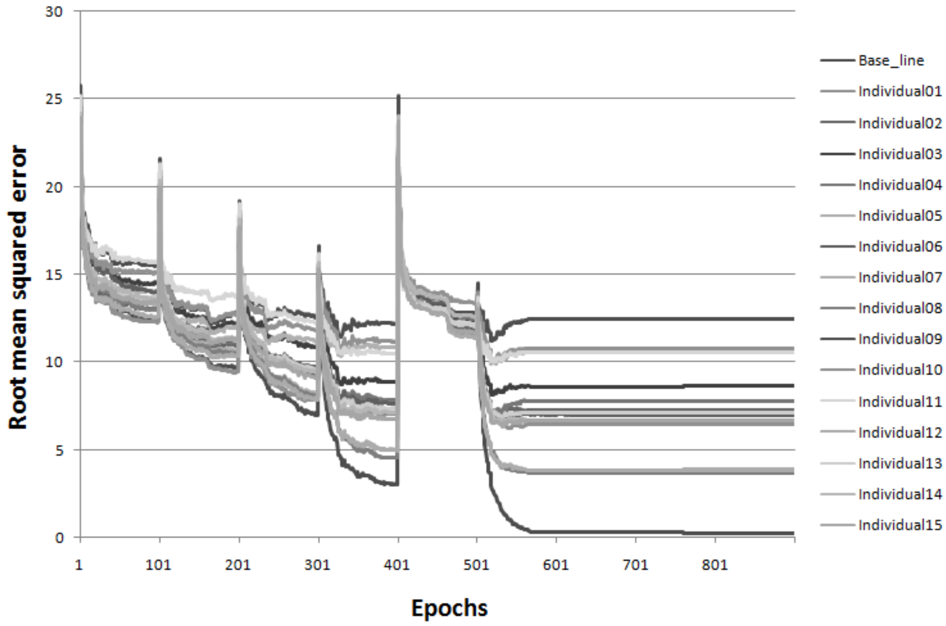

Figure 5. Individualized performance on Task 3

As shown in Figure 3, the students demonstrated similar performances on Task 1, which is contradictory to the conclusion that phonological awareness is an important predictor of a student's learning competences. As previously mentioned, five of the participants were evaluated as extremely poor students, which means that they cannot complete regular tasks. In addition, their English teachers described them in the following manner, "They apparently have some kind of learning disorder; even many extra practices cannot help them to keep up with the normal students' English level." However, their performances on Task 1 converged in a manner similar to that of the other students, which implies that the phonological awareness is not the important cognitive ability that associated with students' L2 learning.

Although student differences in the performance charts related to Tasks 2 and 3 can be observed based on the benchmark line, we still do not know to what degree which abilities will influence learners. Therefore, we conducted an ANOVA of the participants' relative RMSE performances (deviation of the benchmark line). The details are presented in Table 2.

	Task	Disorder		Normal		Excellent			
		M	*SD*	*M*	*SD*	*M*	*SD*	*Sig.*	η^2
1st week	T1	21.8	.03	21.84	.02	21.85	.01	.88	.02
1 epoch	T2	24.38	.06	24.35	.01	24.42	.01	.78	.04
2nd week	T1	18.48	.06	18.53	.02	18.52	.01	.95	.01
100 epoch	T2	18.92	.03	18.89	.01	18.82	.01	.50	.11
	T3	24.22	.33	24.53	.57	24.42	.19	.72	.05
3rd week	T1	16.77	.06	16.64	.00	16.67	.01	.39	.14
200 epoch	T2	15.49	.05	15.62	.03	15.54	.02	.57	.09
	T3	20.22	.45	20.59	.45	18.23	.36	.37	.15
4th week	T1	15.22	.05	15.09	.01	15.17	.01	.43	.13

300 epoch	T2	14.19	.04	14.27	.01	14.07	.02	.17	.25
	T3	17.8	.67	18.22	.37	18.33	.07	.37	.15
5th week	T1	22.42	.04	22.49	.00	22.48	.01	.68	.06
400 epoch	T2	23.43	.01	23.35	.01	23.43	.00	.11	.31
	T3	15.44	.21	15.78	.29	15.84	.16	.38	.15
6th week	T1	12.52	.01	12.41	.03	12.49	.03	.52	.10
500 epoch	T2	12.84	.02	12.88	.01	12.64	.02	.05	.40
	T3	23.66	.06	24.14	.36	23.88	.05	.19	.23
7th week	T1	3.98	1.89	2.44	1.05	2.75	.96	.12	.30
600 epoch	T2	6.27	2.39	3.47	.88	3.19	.88	.00*	.64
	T3	13.17	.23	13.73	.32	13.59	.16	.21	.22
8th week	T1	3.87	1.96	2.32	1.07	2.66	1.12	.13	.29
700 epoch	T2	6.29	2.66	3.46	.99	3.13	1.06	.00*	.62
	T3	8.01	7.75	8.02	12.57	6.66	2.98	.68	.06
9th week	T1	3.65	2.23	1.98	1.37	2.37	1.23	.14	.28
800 epoch	T2	6.35	2.57	3.45	1.00	3.18	1.11	.00*	.62
	T3	8.01	7.75	8.02	12.57	6.65	2.98	.68	.06
Overall	T1	13.19	.18	12.64	.17	12.77	.16	.13	.29
average	T2	14.24	.22	13.31	.11	13.16	.09	.00*	.67
	T3	15.39	1.13	15.58	2.27	15.19	.39	.79	.04

**Sig.*<.05, η^2=.01 (small effect); η^2=.06 (medium effect); η^2=.14 (large effect);

Table 2. ANOVA comparison of the participants' relative RMSEs of each experimental phase

As shown in Table 2, the differentiation of the average RMSEs regarding with Task 2 among three different competence groups becomes bigger and bigger along with the time passing. The significant difference finally appeared in the 7th week, but the significant differences regarding with other two tasks never appeared on the timeline. Therefore, among the three kinds of cognitive abilities involved, only phonological short-term memory has a significant effect on students' learning levels. Although students' performances on Task 3 varied greatly, no evidence suggests that long-term memory is a deciding factor for students' learning competence. Therefore, we can provide their English teacher with the following conclusion through this ANN computational model:

The overall English competence of the students in their first year in this middle school can be predicted by their phonological short-term memory ability. Phonological awareness ability and long-term memory ability cannot be viewed as deciding factors for overall English competence.

By plotting the task 2 ANN trajectories for individuals 02, 04, 05, 11, and 12 (labelled as learning disorder) as well as for 03, 06, 07, 13, and 14 (labelled as excellent) in two charts (Figures 6a and 6b), by observing those two Figures, we can discover the difference between two groups: nearly all disorder students' RMSE lines are above a horizontal line (where y=5), while all excellent student's RMSE are under the line beginning from the 500th epoch and the difference remains during the rest of the epochs. Because the average RMSE for all participants on Task 2 at the 500th epoch is 4.31, the following conclusion can be reached:

If the learning RMSE trajectory of an individual's short-term memory phonological-related ability is above the average line, that individual may be a learner with poor English (L2) overall competency.

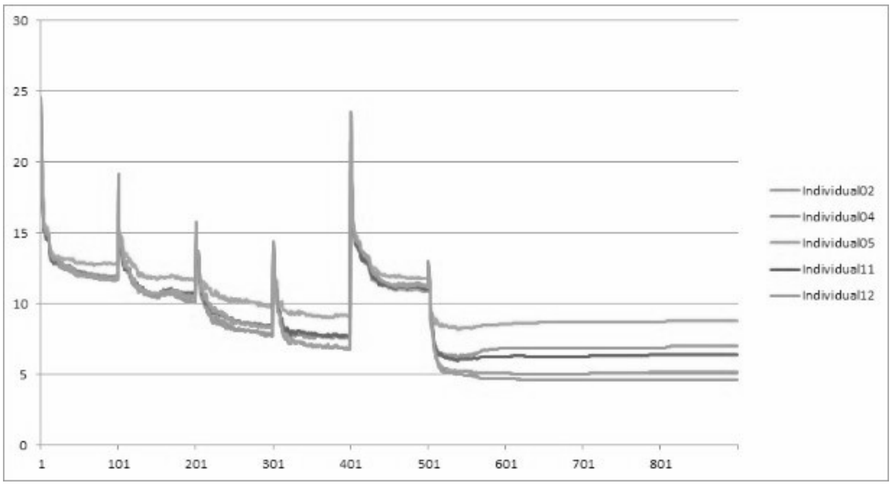

Figure 6a. Learning disorder-labelled participants' performances on Task 2

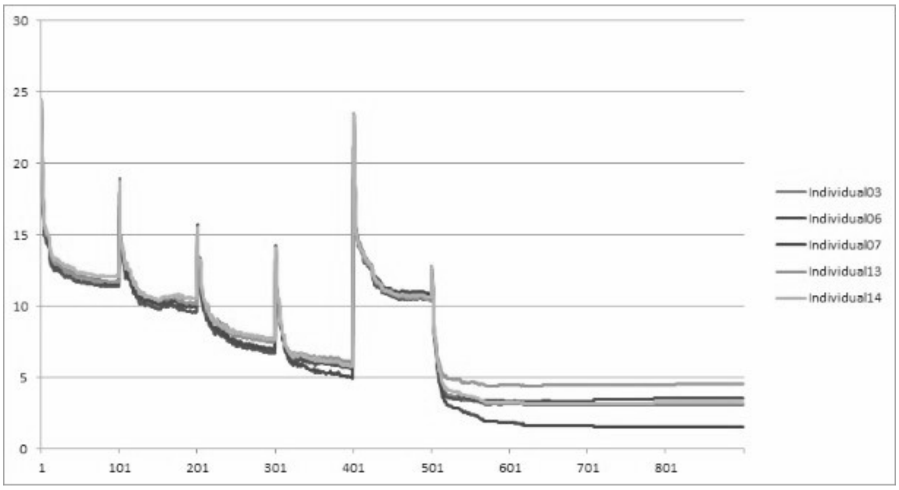

Figure 6b. Excellent-labelled participants' performances on Task 2

This conclusion also can be generated only by observing Figure 3-5. Based on the fact that the virtual learner's learning trajectory represents an optimal learning process of a student, we can directly compare the learners' performances with a virtual optimal learner in a more intuitive way:

If the learning RMSE trajectory of an individual's short-term memory phonological-related ability diverges instead of converges to the virtual student's simulating learning trajectory in the future, that individual may be a learner with poor English (L2) overall competency.

4.2 Verifying the validity and reliability of the ANN computational model against individual cognitive differences

To verify whether the ANN computational model can effectively restore individual cognitive differences, in this section, we conducted another ANOVA analysis of the participants' absolute RMSE (deviation of the correct verbs and their corresponding past tenses) performances. Details are presented in Table 3. ANOVA comparisons conducted in the ANN computational model (Table 2) and traditional experimental method (Table 3) show that the significant results are quite similar, except the appearance of time points in Table 3 that are in the present, while those in Table 2 are in the future. Table 2 and Table 3 indicate that the differences between those labelled as learning disorder, normal and excellent learners, which appear at the 4th and 5th week during the experimental process, can be simulated by the ANN's outputs at the future epochs.

	Task	Disorder		Normal		Excellent			
		M	*SD*	*M*	*SD*	*M*	*SD*	*Sig.*	η^2
1st week	T1	2.92	2.69	2.05	.84	2.25	.61	.49	.11
	T2	4.82	15.59	4.23	8.06	4.24	6.45	.95	.01
2nd week	T1	2.61	7.59	1.92	2.42	2.79	6.39	.83	.03
	T2	4.49	12	2.59	7.15	1.58	.82	.23	.21
	T3	6.64	24.52	4.01	1.86	3.73	16.3	.43	.13
3rd week	T1	2.67	8.08	.67	.84	.14	.1	.09	.33
	T2	4.81	5.63	3.45	1.36	2.97	.86	.21	.22
	T3	5.86	5.29	6.02	22.64	4.01	10.06	.62	.07
4th week	T1	1.83	.43	.54	1.15	2.33	5.16	.20	.23
	T2	8.67	14.29	1.27	.6	2.73	6.56	.00*	.55
	T3	7.51	8.27	8.16	25.69	6.01	8.23	.67	.06
5th week	T1	3.38	9.85	1.82	10.1	.35	.62	.23	.22
	T2	4.9	4.64	2.88	2.73	1.95	.36	.03*	.42
	T3	6.46	14.92	7.84	28.35	4.9	16.95	.59	.08
6th week	T1	4.33	5.39	1.66	1.15	2.06	2.63	.07	.36
	T2	6.31	10.82	3.24	4.67	3.12	3.76	.12	.29
	T3	8.29	13.84	9.45	12.53	8.26	3.56	.76	.04
7th week	T3	10.36	9.72	8.89	24.53	7.78	14.69	.61	.07
Overall	T1	2.96	2.45	1.44	1.62	1.65	.71	.16	.3
average	T2	5.69	2.71	2.94	.85	2.76	.91	.00*	.59
	T3	7.48	7.34	7.39	11.98	5.78	2.81	.55	.09

**Sig.*<.05, η^2=.01 (small effect); η^2=.06 (medium effect); η^2=.14 (large effect);

Table 3. ANOVA comparison of the participants' absolute RMSEs of each experimental phase

	Comparisons	Mean difference	Std. error	95% CI Lower bound	Upper bound
4th week	D vs. N	7.41*	1.69	2.7	12.11
	D vs. E	5.94*	1.69	1.23	10.64
	N vs. E	-1.46	1.69	-6.16	3.24
5th week	D vs. N	2.01	1.01	-.79	4.83
	D vs. E	2.95*	1.01	.13	5.76
	N vs. E	.93	1.01	-1.88	3.74
Overall	D vs. N	2.72*	.77	.57	4.87
	D vs. E	2.90*	.77	.75	5.05
	N vs. E	.18	.77	-1.97	2.32

Table 4. Bonferroni comparison of the absolute RMSEs

	Comparisons	Mean difference	Std. error	95% CI	
				Lower bound	Upper bound
7th week	D vs. N	2.81*	.74	.74	4.88
	D vs. E	3.08*	.74	1.01	5.15
	N vs. E	.27	.74	-1.79	2.34
8th week	D vs. N	2.83*	.79	.63	5.04
	D vs. E	3.16*	.79	.96	5.37
	N vs. E	.33	.79	-1.87	2.53
9th week	D vs. N	2.89*	.79	.70	5.09
	D vs. E	3.17*	.79	.97	5.36
	N vs. E	.27	.79	-1.93	2.46

Table 5. Bonferroni comparison of the relative RMSEs

The reason that the differences appeared at the 4th and 5th week during the experimental process is that students belonging to the disorder team generally can reflect the verbs and their past tenses with some errors, but at Week 4 and Week 5 some of them failed to recall the whole word during the experiment process, which results in a whole '0' coding on this item. The delay of the appearance of the significant differences in the ANN (appeared at Week 7 and 8) can be explained by formula (1). The benchmark line is a virtual learner, who is allowed to make some mistakes during his/her learning process but will eventually converge to an error-free state. Therefore, the individuals' deviation range of the benchmark line is narrower than the deviation range of the correct answer. However, when the performance of the virtual learner becomes error-free, the differences appear among different groups because the $Net_3^m(SV)$ approaches 0. The significant differences in the ANN appeared at Week 9 is a predicting result based on the sample data, which implies that the differences not only appeared currently, but may also last for a long time in the future.

If the contents in Table 2 and Table 3 are not persuasive enough, the subsequent Bonferroni post hoc analysis of the significant results (Table 4 and Table 5) can provide more convincing evidence. In both Table 4 and Table 5, learning disorder learners' RMSE is significantly higher than normal learners and excellent learners. The only difference is that the differentiation of the mean RMSE between students in the disorder group and those in the other two groups in Table 5 are stable, while the differentiation of the RMSE regarding to participants' true performances in Table 4 are changing within a range.

Tables 2–5 indicate that if we allow a machine-learning process to be taken as a benchmark line to reflect the differences between individuals, the results produced by the ANN are as reliable as the results from the traditional methods. It also suggests that teachers can use this ANN computational model-based method to predict the students' potential overall English competencies with a partial data set collected at the beginning stage of the teaching period and can predict students' differences based on the benchmark line.

Results from the ANN simulation and the traditional methods both support the assertion that the phonological short-term memory is important to learners' EFL acquisition. Comparing this result with some previous studies, we can generate some additional important inferences. Service (1992) found that the ability to create and use accurate phonological representations to repeat English sounding pseudowords was a good predictor of learning English as a foreign language. Furthermore, she found the strong correlation between phonological short-term memory and vocabulary acquisition (Service & Kohonen, 1995) (students participated into her experiment were aged 9-10). Some other researches also support this conclusion. For example, Chow etc. (2005) found that one of the phonological processing skills is verbal short-term memory. However Kormos and Safar (2008) suggested that phonological short-term memory plays no role in the achievement in the three major skills related to EFL acquisition for the reason that the participants holding the phonological words in their memory involves other cognitive abilities (the participant in their experiment aged 15-16). Considering the average age of the participants (aged 12-13) in our experiment and the less richness language environment to which they were exposed, the finding about the importance of the phonological short-term memory in our study is consistent with the results concluded by Service. We further argue that the cognitive abilities of which can be used as predictors to students' overall EFL competence may be sensitive to the age of the participants, and thus the ANN simulations regarding cognitive abilities conducted at different time points on a developmental time line may generate different results.

4.3 Evaluating the compound effectiveness of the multi-cognitive abilities

In this section, we will evaluate the compound effects of the multi-kinds of cognitive abilities on L2 through observing participants' individualized trajectories regarding with three cognitive tasks. The relative ANN RMSE results for each individual are illustrated in Figure 7, they are RMSEs regarding to Task 1(blue lines), Task 2 (red lines) and Task 3 (green lines), respectively. Lines in Figure 7 are the same lines in Figure 3, 4 and 5, and Figure 7 is a transformation of Figure 3, 4 and 5. It can be observed from Figure 7 that under the same encoding and script mechanism, although most participants' long-term memory performances are obviously poorer than their phonological awareness and short-term memory performances, there are still some exceptions. For example, student 12 has a good compound cognitive ability compared with other learning disorder students but is evaluated as an extremely poor student. We investigated this phenomenon by interviewing all participants and found that motivation of learning is the key factor to influencing his English competence. The opposite examples would be students 9 and 10, who have poor long-term memory ability but maintain high enthusiasm for English learning, which makes them achieve comparatively good results. However, their limited cognitive abilities still prevent them from being excellent learners. The individual simulation trajectories may help English teachers to quickly find abnormal situations, such as student 12.

In addition to motivation factor, students 11, 9, 10 and 3' individualized ANN results gave us another hypothesis about the effectiveness of compound cognitive abilities on L2. Although no evidence suggests that long-term memory capacity matters in English (L2) learning, student 11 (with a poor long-term memory ability) was evaluated as an extremely poor student even though she has a rather good short-term memory ability; students 9 and 10 also have rather poor long-term memory abilities compared with other normal students; student 3's long-term memory ability is comparatively poorer than the other students in the excellent group, however, his overall competence in English is as good as other excellent students. Among all students with poor long-term memory abilities, we noticed that although student 11's short-term memory ability is better than that of other students with learning disorders, her simulation line is still above the mean line while students 9, 10 and 3's short-term memory lines are below the mean line. In addition, student 3's phonological short-term memory is the best of all, and better than most other excellent students. Therefore, we can make a reasonable inference regarding the compound effectiveness of the short-term memory ability and long-term memory ability on L2 based on these qualitative data:

Phonological short-term memory is not only a deciding factor for English learning, but it also can generate some compensations for long-term memory ability. Thus, if a student's long-term memory is not too bad, this ability can be compensated by the higher short-term memory capacity.

Therefore, it can be predicted that there will be a high risk that student 9 and 10 would fall behind if they lose their strong learning motivation because their short-term memory ability is not good enough to compensate for their disadvantages in long-term memory capacity.

4.4 Using the ANN computational model in an online platform

To improve the usability of the ANN computational model for English teachers, it has been wrapped into functions that are embedded in an online platform to provide simulation, evaluation and prediction services for teachers. Teachers upload the records of the students to the platform to generate reports through the interactive interfaces provided by system. As illustrated in Figure 8 to 11, Figure 8 is a snapshot of the introduction page, Figure 9 illustrates the file uploading interface, Figure 10 is a snapshot of the report generating option page, and Figure 11 is a snapshot of the final reports generated by the system. Until now, the website is only served to local users and cannot be visited by ordinary users outside the campus.

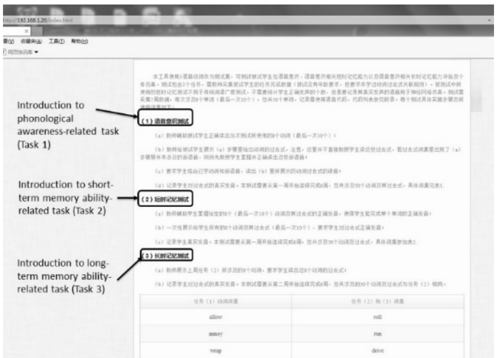

Figure 8. A snapshot of the introduction page

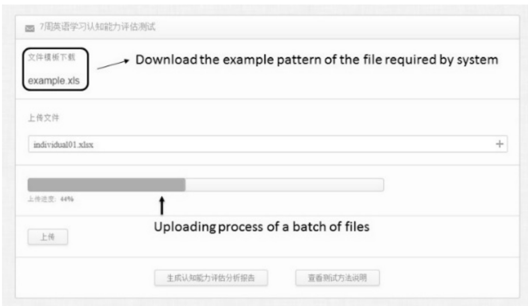

Figure 9. A snapshot of the file uploading interface

Figure 10. A snapshot of the report generating options

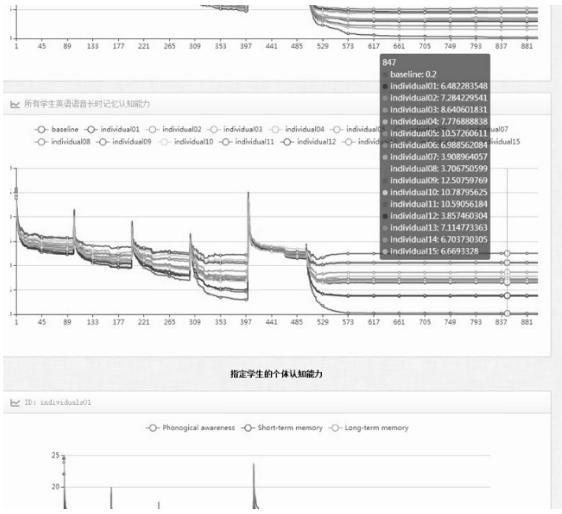

Figure 11. A snapshot of the final reports generated by the system

5. Conclusions and future work

In this paper, we proposed an ANN computational model-based method to help English teachers to quickly evaluate and observe learners' cognitive abilities, which are important in their English (L2) acquisition. The ANN computational model not only equips English teachers with the ability to find the predicting factors to learners' overall English competences but also provides teachers with the ability to identify abnormal situations based on observing students' individualized ANN trajectories. Finally, by observing the compound effects of cognitive factors using the same evaluation scale, teachers can generate new hypotheses about the mutual relationships among the phonological awareness, phonological short-term memory and long-term memory abilities of their students. These related functions can provide English teachers with a much prudential and scientific examination regarding their current students' cognitive abilities before they design and apply cognitive ability-related intervention strategies for their L2 pedagogical activities.

The experimental results show that the ANN has a good restoring ability to account for the significant features among different clustered (learning disorder, normal and excellent) individuals. Table 2 and Table 3 show similar results on whether the significant differences with regard to three kinds of cognitive abilities are existing among learners with different learning competencies. And both results support the argument that phonological short-term memory ability is important to participating learners' EFL acquisition while the other two (phonological awareness and phonological long-term memory) are less important. Therefore, based on the reliable result rebuilt by the ANN computational model, following conclusion can be generated:

- The overall English competence and learning level of the students in their first year in this middle school can be predicted by their phonological short-term memory ability. Phonological awareness ability and long-term memory ability cannot be viewed as the deciding factors for overall English competence.

In addition to the above conclusion, Table 4, 5 and Figure 6 also suggest that the learners with learning disorder have significant higher RMSE values compared with those belonged to normal and excellent groups. Thus, by reviewing the simulated RMSE trajectory of a student can predict this student's overall English learning competence, and the observing rule can be described as follow:

- If the learning RMSE trajectory of an individual's short-term memory phonological-related ability is above the average line, that individual may be a learner with poor English (L2) overall competency.

After analysing some qualitative examples of the participating students' individualized trajectories, an inference is generated:

- Phonological short-term memory can generate some compensations for long-term memory ability. If a student's long-term memory is not too bad, this ability can be compensated for by a higher short-term memory capacity.

Of course, the above three conclusions are only suitable for the students in their first year in the Zongbei Experimental Middle School. Because the ANNs simulated the environmental configurations represented by the participating 15 students. If other teachers provide different samples to build their own ANNs, different conclusions might be reached. It should be noted that the control of the experimental process of capturing sample data may also have an influence on the accuracy of the simulated results. As mentioned earlier in this paper, some of the students with learning disorder sometimes may fail to recall a whole word when they were going through Task 2 although the whole experiment is under a strictly controlled environment (sample the participants one by one and keep the experimental environment quiet). This phenomenon reveals a hidden threat to the internal validity of the results generated by the ANN computational model: if the participant's attention is distracted from the tests by the outside factors when they are going through related tasks, the unexpected loss of the information may be incurred. Therefore, it is suggested that teachers should try their best to eliminate the outside interfering factors when they are collecting sample data, because the better controlling the experimental processes, the more accurate result will get from the ANN computational model. If English teachers experience difficulty in strictly controlling the process of sample data collection, a visual-memory test may be a substitute as it can be executed by other practitioners with a psychology background, making it a feasible solution for avoiding the aforementioned hidden threat to the internal validity. However, there is a risk in adopting a general short-term memory test as it may not be an effective indicator of reflecting and predicting students' L2 performances.

In addition to providing EFL teachers with the simulations on their students' learning effect, another prospective application of ANN computation model is to help learners improve their language learning competencies through simulating possible 'behavioural intervention' solutions. For example, if the simulations of the cognitive abilities reveal they are plastic and can be improved through appropriate interventions, the ANN-based computational model can be used to simulate the intervening strategies, and observing the possible outcomes by adding extra training data to an ANN before those strategies are used in classroom. In order to explore this broader usage of the ANN computational model, now, we are conducting a similar experiment on a group of primary students (mean age=6) and accompany with an intervention plan for classroom teachers to observe whether the simulation of the intervention strategy is practical.

Finally, the limitations of the proposed computational model-based method should be mentioned. One of them is that the sample data required requires at least four weeks to collect, which is time-consuming. Our another ongoing work is attempting to simplify the sample data collection procedure; another limitation of the computational model is in simulating other cognitive factors because not all cognitive abilities can be modelled by verbs and their past tenses. To evaluate and investigate individual differences covering more types of cognitive factors related to second-language acquisition, new methods should be explored.

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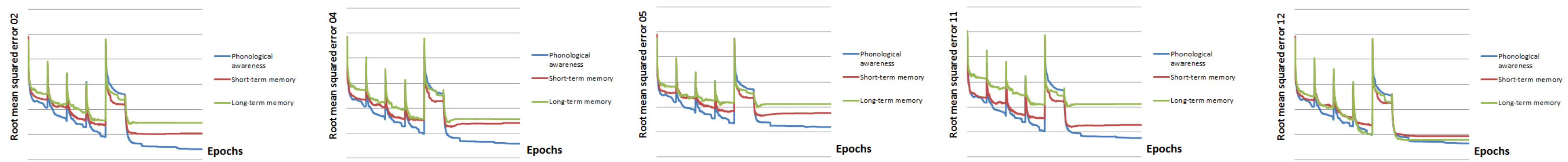
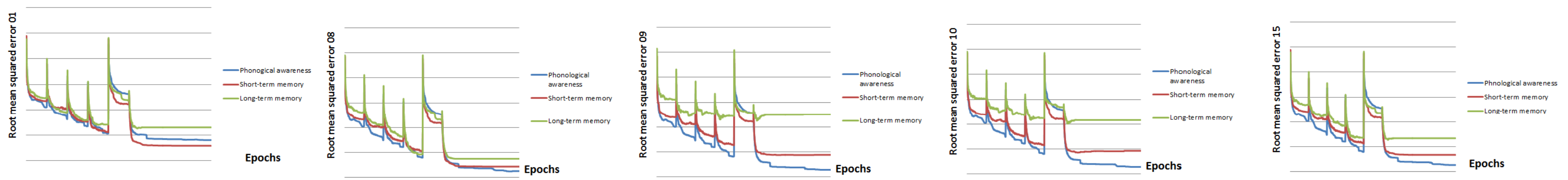
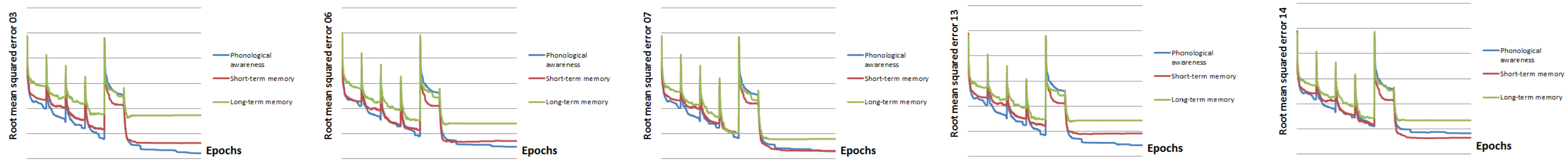


Disorder learners' ANN simulation



Normal learners' ANN simulation



Excellent learners' ANN simulation

Figure 7. ANN simulations of the participant students learning trajectories with regard to three cognitive tasks

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Appendix A

Phoneme coding mechanism used in this paper

Symbol	19 bit coding																			Phoneme
E	1	0	1	1	1	0	1	0	0	0	0	0	1	1	0	0	0	1	0	/i:/ in beet
i	1	0	1	1	1	0	1	0	0	0	0	0	0	1	1	0	0	0	0	/I/ in bit
O	1	0	1	1	1	0	0	0	1	0	0	0	0	0	1	0	1	1	1	/o/ in boat
^	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	/L/ in but
U	1	0	1	1	1	0	0	0	1	0	0	0	0	1	0	0	1	1	1	/u:/ in boot
u	1	0	1	1	1	0	0	0	1	0	0	0	0	1	1	0	1	0	0	/U/ in foot
A	1	0	1	1	1	0	1	0	0	0	0	0	1	0	1	0	0	1	1	/e/ in bait
e	1	0	1	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	/e/ in bet
I	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	/ai/ in bite
@	1	0	1	1	1	0	1	0	0	0	0	0	1	0	0	1	0	0	0	/ae/ in bat
#	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	1	1	0	1	/au/ in bout
*	1	0	1	1	1	0	0	0	1	0	0	0	0	0	1	0	1	0	0	/O/ in bought
!	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	/ ɔ / in dog
F	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	1	1	1	/ ɔi / in boy
C	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	/a:/ in bath
D	1	0	1	1	1	0	0	0	0	0	0	0	0	1	0	0	1	1	1	/ ʊə / in tour
K	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	1	/ eə / in hair
$	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	/ ə / in about
b	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	/b/ in bill
p	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	/p/ in spill
d	0	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	/d/ in dill
t	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	/t/ in still
g	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	/g/ in gill
k	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	/k/ in skill
v	0	1	0	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	/v/ in veal
f	0	1	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	/f/ in feel
m	1	1	0	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	/m/ in mill
n	1	1	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	/n/ in nil
G	1	1	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	/ ŋ / in ring

T	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	/ ð / in thigh
H	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	/ θ / in thy
z	0	1	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	/z/ in zeal
s	0	1	0	1	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	/s/ in seal
w	1	0	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	/w/ in witch
l	1	1	0	1	1	0	1	1	0	0	0	1	0	0	0	0	0	0	0	/l/ in leaf
r	1	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	/r/ in reef
y	1	1	0	1	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	/j/ in you
h	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	/h/ in high
L	0	1	0	1	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0	/ ʃ /
?	0	1	0	1	1	0	1	0	0	1	0	0	1	1	0	0	0	0	0	/ʒ/
M	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	/g/
J	0	1	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	/ tʃ /
P	1	0	1	1	1	0	0	0	0	0	0	0	1	0	1	0	0	1	0	ə:
Q	1	0	1	1	1	0	0	0	0	0	0	0	1	0	1	0	0	1	1	iə
R	0	1	0	0	0	0	0	0	1	0	0	1	1	1	0	0	1	0	0	tr
V	0	1	0	0	0	0	1	1	0	1	0	0	0	1	0	0	0	0	0	ts
N	0	1	0	0	1	0	0	0	1	0	0	1	1	1	0	0	1	0	0	dr
q	0	1	0	0	1	0	1	1	0	1	0	0	0	1	0	0	0	0	0	dz
B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Null
X	1	0	1	0	0															[d]
Y	0	1	0	1	0															[t]
Z	1	1	0	0	1															[ed]
W	0	0	0	0	0															Null

Appendix B

Verbs and past tenses involved in task 1

Verbs			Past tenses			
ə	l	aʊ	ə	l	aʊ	X
ə	n	ɔɪ	ə	n	ɔɪ	X
ə	p	ɪə	ə	p	ɪə	X
r	æ	p	r	æ	p	Y
b	eɪ	k	b	eɪ	k	Y
b	ɑ:	k	b	ɑ:	k	Y
b	ɜ:	n	b	ɜ:	n	X
k	ɔ:	l	k	ɔ:	l	X
k	æ	tʃ	k	ɔ:	t	W
ə	b	eɪ	ə	b	eɪ	X
k	ɔ:	z	k	ɔ:	z	X
tʃ	eɪ	s	tʃ	eɪ	s	Y
tʃ	æ	t	tʃ	æ	t	Z
l	aɪ	t	l	aɪ	t	Z

p	ɪə	s	p	ɪə	s	Y
l	e	t	l	e	t	W
l	aɪ	k	l	aɪ	k	Y
l	ɪ	v	l	ɪ	v	X
l	ɒ	k	l	ɒ	k	Y
h	æ	ŋ	h	ʌ	ŋ	W
l	ʌ	v	l	ʌ	v	X
m	iː	t	m	e	t	W
m	ɪ	s	m	ɪ	s	Y
n	iː	d	n	iː	d	Z
ɒ	f	ə	ɒ	f	ə	X
s	ɪ	ŋ	s	æ	ŋ	W
ɔː	d	ə	ɔː	d	ə	X
p	æ	k	p	æ	k	Y
p	ɑː	k	p	ɑː	k	Y
p	ɑː	s	p	ɑː	s	Y
ɡ	l	uː	ɡ	l	uː	X
p	ɪ	k	p	ɪ	k	Y
tʃ	ɒ	p	tʃ	ɒ	p	Y
k	ʌ	m	k	eɪ	m	W
k	ʊ	k	k	ʊ	k	Y
k	ɒ	f	k	ɒ	f	Y
p	iː	l	p	iː	l	X
k	r	aɪ	k	r	aɪ	X
p	l	eɪ	p	l	eɪ	X
p	ʊ	l	p	ʊ	l	X
p	ʊ	ʃ	p	ʊ	ʃ	Y
r	eɪ	s	r	eɪ	s	Y
r	eɪ	n	r	eɪ	n	X
r	ɪ	ŋ	r	æ	ŋ	W
r	ʌ	ʃ	r	ʌ	ʃ	Y
s	eɪ	l	s	eɪ	l	X
p	ʊ	t	p	ʊ	t	W
r	aɪ	d	r	əʊ	d	W
g	e	t	ɡ	ɔ	t	W
r	eɪ	z	r	eɪ	z	X

Appendix C

Verbs and past tenses involved in task 2 and task 3

Verbs			Past tenses			
r	əʊ	l	r	əʊ	l	X
r	ʌ	n	r	æ	n	W
dr	e	s	dr	e	s	Y
dr	aɪ	v	dr	əʊ	v	W

dr	ɔ	p	dr	ɔ	p	Y
f	eɪ	s	f	eɪ	s	Y
f	eɪ	l	f	eɪ	l	X
f	ɔː	l	f	e	l	W
b	ɔɪ	l	b	ɔɪ	l	X
f	e	l	f	e	l	X
f	ɪ	l	f	ɪ	l	Z
f	ɪ	t	f	ɪ	t	W
t	eɪ	k	t	uː	k	W
h	iː	t	h	iː	t	Z
k	ɪ	d	k	ɪ	d	Z
f	uː	l	f	uː	l	X
t	aɪ	p	t	aɪ	p	Y
j	uː	z	j	uː	z	X
w	eɪ	t	w	eɪ	t	Z
w	eɪ	k	w	əʊ	k	W
w	ɔː	k	w	ɔː	k	Y
w	ɒ	ʃ	w	ɒ	ʃ	Y
w	ɒ	tʃ	w	ɒ	tʃ	Y
w	eɪ	v	w	eɪ	v	X
l	ʊ	k	l	ʊ	k	Y
w	aɪ	p	w	aɪ	p	Y
w	ɜː	k	w	ɜː	k	Y
r	aɪ	t	r	əʊ	t	W
s	t	eɪ	s	t	eɪ	X
s	t	ɔː	s	t	ɔː	X
s	uː	t	s	uː	t	Z
s	ɜː	f	s	ɜː	f	Y
t	ɔː	k	t	ɔː	k	Y
g	aɪ	d	g	aɪ	d	Z
h	aɪ	k	h	aɪ	k	Y
h	əʊ	p	h	əʊ	p	Y
dʒ	ɔɪ	n	dʒ	ɔɪ	n	X
k	ɪ	l	k	ɪ	l	X
k	ɪ	s	k	ɪ	s	Y
n	ɒ	k	n	ɒ	k	Y
l	ɑː	f	l	ɑː	f	Y
l	ɜː	n	l	ɜː	n	X
tr	iː	t	tr	iː	t	Z
t	ɜː	n	t	ɜː	n	X
b	aɪ	d	b	aɪ	d	Z
f	iː	d	f	e	d	W
g	r	əʊ	g	r	uː	W
k	r	əʊ	k	r	əʊ	X

k	ʌ	t	k	ʌ	t	W
r	e	d	r	e	d	W