International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 1757-1768

https://doi.org/10.70517/ijhsa463138

Research on the Development of Cognitive Transfer Ability Based on Meta-Learning Algorithm in College English Teaching for the Cultivation of Foreign Language Talents in the New Era

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Abstract Influenced by the influence of the mother tongue learning method on the English learning method, students under the current university English teaching mode are difficult to make effective English language application in real life. This paper is guided by the migration theory. By guiding students to apply their existing learning methods to English language learning, it improves students' metacognitive level, which is the main realization method of metacognitive transfer strategy. Meanwhile, on the theoretical basis of metacognitive transfer strategy, the deep learning technique of meta-learning is further proposed. Using meta-learning as a separate learning migration bridge between students and knowledge points in the knowledge point area, the meta-learning network module is constructed to complete the formation of the cognitive migration model based on the meta-learning algorithm. At the same time, the metacognition-based problem solving process is analyzed and the migration-based problem solving process is extended for the difficulties encountered by the students in the stage of the learning migration process. Under the tutelage of the cognitive migration model based on meta-learning algorithm, the students obtained higher mean scores of 2.5 and above on the nine variables of learning effect evaluation, indicating that the model can effectively assist in the enhancement of the teaching effect of college English.

Index Terms metacognitive transfer, meta-learning algorithm, college English teaching, learning transfer

I. Introduction

With the rapid development of science and technology and global economy, English, as a world language, has gained more and more application space, which also puts forward higher and higher requirements for the cultivation of English talents in Chinese universities [1], [2]. As far as the current comprehensive application ability of university English majors is concerned, there are still some students who are influenced by the habit of using their mother tongue, which largely affects the effect of English learning [3], [4]. Therefore, it is necessary to study the teaching way of English learning cognitive transfer ability from the perspective of developing cognitive transfer ability, so as to help students make full use of the positive effect of language transfer in order to cultivate foreign language talents in the new era [5]-[7].

Learning cognitive transfer ability refers to the positive or negative effect of one kind of learning on another kind of learning, which allows learners to analyze the newly accepted knowledge on the basis of the existing knowledge structure, and then to realize the intersection and transfer of new and old knowledge on the basis of the analysis [8]-[10]. Migration is a phenomenon inevitably produced by learners in the learning process, as long as there is a learning behavior, the phenomenon of migration is inevitable [11]. The learner's ability to transfer is both a fresh application of existing knowledge and a condition for deepening and consolidating existing knowledge [12]. If learners have high transfer competence, the process of learning English will be smoother in the future [13]. However, the improvement of transfer ability cannot be realized in a short time [14]. Teachers need to focus on the important driving role of language transfer in English learning for different students, starting from their objective situation of language transfer, tailoring the teaching to the students' needs, and focusing on the important driving role of language transfer in English learning, and then guiding them through scientific and effective teaching strategies, so as to make them better utilize the role of language transfer in English learning, and to obtain a more desirable learning efficiency and learning effect [15]-[18].

This paper firstly elaborates the basic theory of metacognitive concept, then develops its application methods and processes in English teaching, and puts forward the metacognitive migration strategy of English teaching.

Subsequently, it focuses on the different learning methods of students, based on the meta-learning algorithm for students to migrate the bridge learning, and designs the meta-learning network module, so as to construct the cognitive migration model based on the meta-learning algorithm. It also discusses the steps to solve the learning problem based on the metacognitive approach. Referring to its solution method, the migration-based problem solving process is proposed. Finally, it explores the differences in the learning of syntactic functions of English progressives among different English learners, and develops the validity test of the meta-learning algorithm and cognitive transfer model.

II. A cognitive transfer model based on meta-learning algorithms

II. A. Metacognitive transfer strategies

Metacognition is the awareness of cognition, i.e., an individual's awareness and control of his or her own cognitive processes and outcomes. In its essence, metacognition is the individual's self-awareness and self-regulation of cognitive activities. It has two independent but interrelated components: knowledge and concepts of cognitive processes (stored in long-term memory). Regulation and control of cognitive behavior (stored in working memory). The two main components are metacognitive knowledge and metacognitive control. The use of metacognition in psychology is mainly characterized by three strategies: planning, monitoring and regulating. The metacognitive transfer strategy proposed in this paper refers to the application of metacognitive strategies used by students in learning other knowledge to English language learning by using appropriate teaching tools as mediating variables in the teaching process.

The main role of metacognitive strategies is to help learners improve their ability of independent learning. In order to achieve this purpose, teachers usually combine the characteristics of students with cognitive training in the teaching process. Specific operation process: (1) Determine the goal: including immediate and long-term goals. (2) Make a plan: make a suitable plan according to the theory of the nearest development area. (3) Selection of attention: Determine the focus to be listened to in class. (4) Self-monitoring: Monitor your own understanding, task completion, and regulation methods. (5) Self-assessment: Individual assessment of learning after applying the transfer. (6) Pre-study and review. (7) Seek help. After metacognitive training, students are often able to form a set of learning methods suitable for themselves. The metacognitive transfer strategy requires English teachers to reasonably apply students' existing learning methods to English learning according to the characteristics of the English language and with appropriate teaching means as the mediating variable when teaching English knowledge.

Taking reading comprehension teaching as an example, when learning the native language, teachers often train students in reading comprehension. Students gain the ability to solve the type of questions independently. English, as a foreign language, has its own unique vocabulary system, habits of thought, and ways of expression, and it is difficult for most students to solve such questions in English independently at the beginning. Teachers should choose appropriate teaching methods in English teaching to extend the independent problem-solving ability acquired by students in their mother tongue learning to English learning, so as to improve the students' transfer ability and benefit them throughout their lives. The following methods can be adopted: firstly, choose a number of short reading materials as experimental tools. Secondly, teachers and students work together to complete the reading of these materials and discuss reading skills and problem solving methods. Third, the students will summarize these reading skills and reading methods. Fourthly, students will choose the more difficult reading materials and use the reading skills and methods they have learned to complete the reading of these materials to form the migration of reading skills and methods, so as to improve the reading level. Through the metacognitive transfer training, students' metacognitive level in reading is significantly improved, and they also consciously or unconsciously apply this transfer to the monitoring and regulation of other learning activities.

One of the purposes of English language teaching is to enable students to learn to use effective metacognitive strategies. With the guidance of metacognitive transfer strategies, teachers are able to teach students to use metacognitive strategies to improve their performance. Students can learn to think about their own thought processes and apply specific learning strategies to difficult tasks. According to the metacognitive transfer strategy, teachers can set reasonable teaching goals and prepare reasonable teaching plans based on analyzing the characteristics of learners and the English language subject. The study of metacognitive transfer strategies is of great significance to English language teaching.

II. B. Meta-learning

Meta-learning, also known as learning to learn, is centered on the idea of obtaining some generalized “meta-knowledge” by summarizing and abstracting past learning experiences, and applying this meta-knowledge to new learning tasks. Meta-learning is categorized into three main approaches: metric-based approaches, mapping the dataset to a meta-knowledge space, and meta-knowledge extraction transformed into a spatial transformation problem. Gradient based methods such as MAML. Parameter generation based methods.

MAML is a classic implementation of meta-learning. MAML first divides the dataset into n small subsets, each subset is then divided into training and test sets. The model first computes the loss on the support set of the subset and updates the parameters, then computes the loss of the query set and updates the parameters of the meta-learning with the second loss.The schematic of gradient descent of MAML is shown in Fig. 1. .

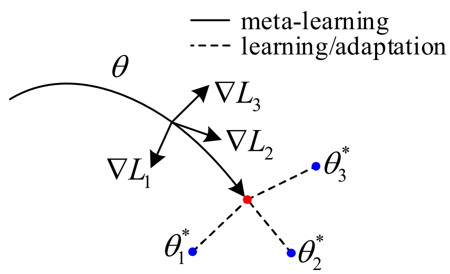


Figure 1: MAML gradient descent signal

In cross-domain recommendation, learning migration bridges is often required when performing knowledge migration, so parameter generation-based meta-learning can be utilized to quickly learn personalized migration bridges for users and items. The model proposed in this paper, on the other hand, utilizes parameter generation-based meta-learning to learn personalized migration bridges for users and items when their representations are migrated between domains, thus preserving the personalized preferences of the users and items and improving the recommendation effect.

II. C.Meta-learning network module

The meta-learning network module fuses intra- and inter-domain user and item representations $E^d_{intra_u}$, $E^i_{intra_i}$, E_{inter_u} and E_{inter_i} are fused. Meanwhile, considering the user- and item-specific feature migration, meta-learning is adopted to learn personalized migration bridges for each user and item, which is mainly divided into three modules: meta-learning layer, personalized bridge layer and representation fusion layer, and the meta-learning network module is shown in Fig. 2.In this section, the meta-learning network module will be introduced in detail.

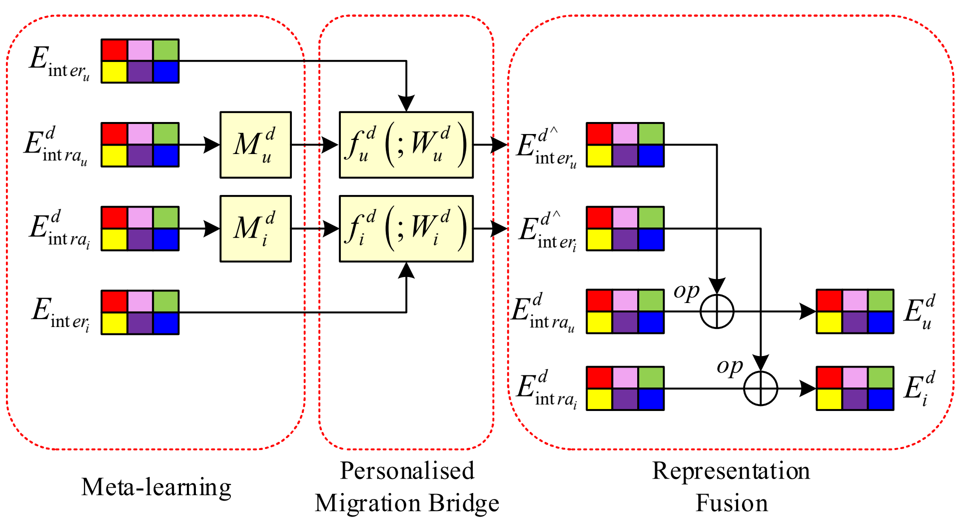


Figure 2: Meta-learning network module

The meta-learning layer will utilize the user and item representations $E^d_{intra_u}$ and $E^d_{intra_i}$ of the domain obtained by learning from the graph embedding layer for training the meta-learning network, which is a three-layer neural network, and the meta-learning layer is shown in Fig. 3. For the domain $d \in \{a,b,c\}$, there are meta-learning networks M_u^d and M_i^d, and the personalized migration bridge network parameters W_u^d are obtained through the meta-learning layer as in equation (1):

$$
\begin{aligned}
W_u^d &= M_u^d\left(E_{intra_u}^d;\phi\right) \\
W_i^d &= M_i^d\left(E_{intra_i}^d;\phi\right)
\end{aligned}
\tag{1}
$$

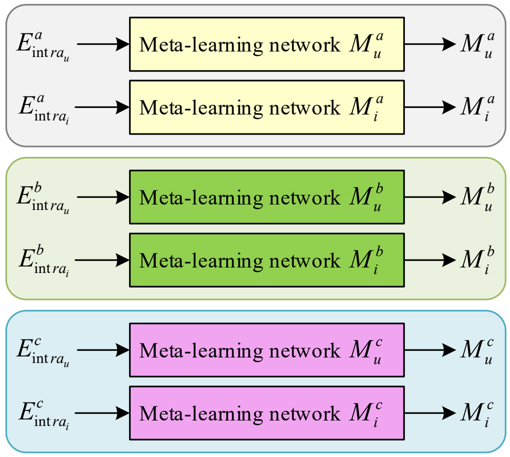


Figure 3: Meta-learning layer

The personalization bridge layer uses the W_u^d, and $d \in a,b,c$ obtained by the learning of the meta-learning layer to obtain the personalization migration functions f_u^d and f_i^d of users and items as in equation (2). . The functions use a one-layer neural network layer, where $W_u^d \in \mathbb{R}^{k^2}$ is dimensionally transformed to $k \times k$ to obtain $W_u^d \in \mathbb{R}^{k\times k}$[52].

$$
\begin{aligned}
&f_u^d\left(\cdot;W_u^d\right) \\
&f_i^d\left(\cdot;W_i^d\right)
\end{aligned}
\tag{2}
$$

The personalized migration bridge is shown in Fig. 4. For the inter-domain user and item representations E_{interu}^d and E_{inter}^i, the inter-domain user and item representations $E_{inter}^{d\wedge}$ and $E_{inter}^{d\wedge}$ can be obtained after the migration function as in Equation (3).

$$
\begin{aligned}
E_{inter_u}^{d\wedge} &= f_u^d\left(E_{inter_u}^d;W_u^d\right) \\
E_{inter_i}^{d\wedge} &= f_i^d\left(E_{inter_i}^d;W_i^d\right)
\end{aligned}
\tag{3}
$$

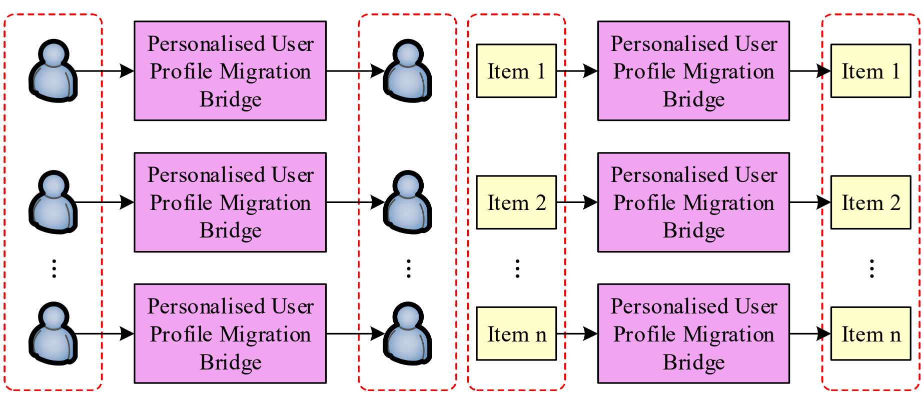


Figure 4: Personalized transfer bridge

The representation fusion layer fuses intra- and inter-domain user and item representations to obtain E_u^d and E_i^d separately for each domain, where $d \in \{a,b,c\}$. As in equation (4), where $f(\cdot)$ is the aggregation function, the aggregation can be done in the way of splicing, averaging, summing, maximum and minimum values.

$$
\begin{aligned}
E_u^d &= f\left(E_{\text{inter}_u}^{d\wedge}, E_{\text{intra}_u}\right), d \in \{a,b,c\} \\
E_i^d &= f\left(E_{\text{inter}_i}^{d\wedge}, E_{\text{intra}_i}\right), d \in \{a,b,c\}
\end{aligned} \tag{4}
$$

III. Links between learning transfer and problem solving

III. A. Problem solving process based on metacognition

From the previous section, we can know that problem solving is a cognitive process. Migration behaviors in problem solving situations are closely related to metacognitive functions. For example, transfer can be used as a self-improvement tool, enabling students to direct their attention, set and adjust their goals, and direct their learning more effectively. The more people control and monitor the strategies they use, the better they become at problem solving. The three metacognitive strategies that support these functions are (1) self-direction, which helps students identify the components of a problem before executing a solution to it. (2) Self-questioning guided by self-talk. The purpose of self-questioning is to provide a structured analysis of the problem. (3) Self-monitoring that encourages students to control the execution process.

In problem solving, metacognition is used to support the cognitive level by activating the factors of monitoring and control. In the general process of metacognitive problem solving, there are three components: integrating knowledge, conceptualizing knowledge, and choosing and formulating solutions. Scholars have determined the reliability of the problem solving process by experimenting with the problem solving steps of metacognition through mathematical problem solving experiments, dividing the metacognitive problem solving process into six steps, which are (1) Problem identification. (2) Problem formulation. (3) Planning how to solve. (4) Generating the solution. (5) Evaluation. (6) Feedback after problem solving. The metacognitive problem solving process is shown in Figure 5.

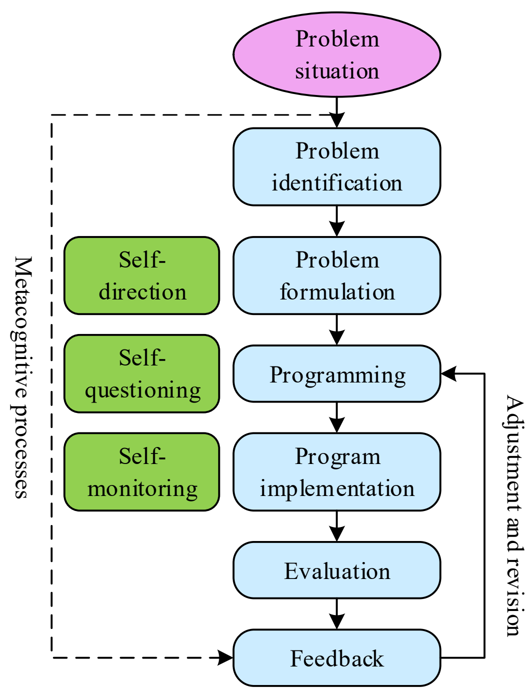


Figure 5: Metacognitive problem solving process

III. B. Migration-based problem solving process

The following conclusions have been drawn from the sorting out of learning transfer and problem solving: first, learning transfer and problem solving are interdependent and mutually reinforcing. Learning transfer is the basis of problem solving and can promote problem solving, and in turn problem solving stimulates the occurrence of learning transfer. Secondly, under the condition of transfer, there is a correspondence between the problem solving process and the learning transfer process. Learning transfer and problem solving are inseparable, and under the condition of transfer, they can be almost equivalent. Therefore, under the condition of migration, the strategies and methods of the problem solving process can become the tools to promote learning migration.

Problem solving and learning transfer processes are mutually reinforcing and fit each other to some extent in terms of process and purpose. Problem solving occurs in three situations: first, the problem situation to be solved is exactly the same as the previously encountered situation, and the previous experience, knowledge and skills can be used directly. The second is that the problem situation to be solved is similar but not identical to the previous problem situation, and requires some transformation and innovation of the previous experience, knowledge and skills called upon before they can be used to solve the problem in the new situation. This situation corresponds to the near transfer in learning transfer. Third, the problem situation to be solved is not similar to the previous problem situation and is completely different, which requires not only the transformation and innovation of the previous experience, knowledge and skills, but also some kind of processing of the new and completely different problem situation so that it can be related to the previous knowledge and then the problem can be solved. This situation corresponds to the far transfer in learning transfer. However, the process of problem solving remains the same regardless of the context in which it occurs. When the context in which problem solving occurs is similar but not identical to the previous context, it prompts the conditions for near migration to occur, and near migration begins to occur. And when the context in which problem solving occurs is completely different from the previous context, it prompts the conditions for far migration to occur, and far migration begins to occur. In order to present the correspondence between the problem solving process and the migration process more clearly, the problem solving process is constructed based on the migration process under the migration condition. The migration-based problem solving process is shown in Figure 6.

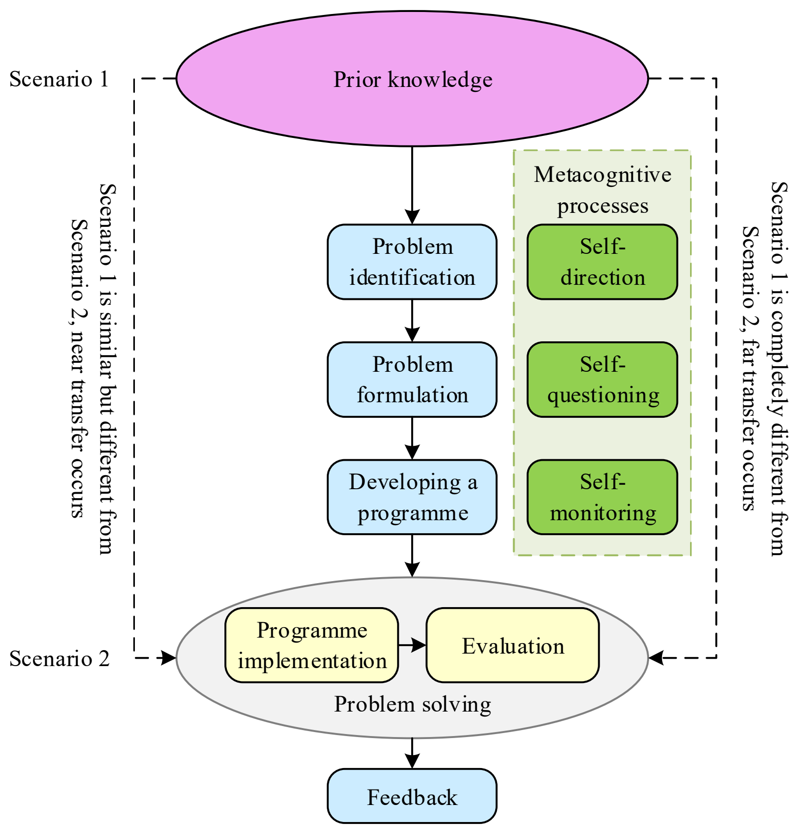


Figure 6: Migration-based problem solving process

Although learning transfer and problem solving are quite similar in terms of connotation, purpose and process, and have a high degree of fit. Among them, the occurrence of far and near migration are the two core paths of learning migration. And all other types of migration can be attributed within the two paths of far and near migration. However, the problem solving process still fails to show the process of learning migration completely. The main reason is that the problem solving process has not been able to bring out the process of how knowledge is invoked, transformed, and innovated in the learning migration process. In particular, the two steps of problem identification and problem formulation do not reflect the state of knowledge invocation and the process of how knowledge is transformed into useful knowledge that can be used to solve problems in new contexts. This process of situation identification and knowledge extraction is an indispensable and important part of the learning transfer process. Although the problem-solving process and the learning transfer process cannot be completely equated, the problem-solving process has great implications for the improvement of the learning transfer process. In the process of problem solving, "plan formulation", "program implementation", "evaluation" and "feedback", the process and feedback mechanism of the problem being solved are clearly displayed, which can be an important reference for the "problem solving" part of learning transfer.

IV. Testing and Evaluation of Cognitive Migration Models

In order to verify the effectiveness of the cognitive transfer model based on the meta-learning algorithm, this chapter firstly develops a comparison of the completion accuracy of the meta-learning algorithm with similar algorithms on a variety of task sets, and secondly, designs an ablation experiment of the learning rate to test the operational performance of the cognitive transfer model. Based on the correlation between learning transfer and problem solving, this chapter explores the transfer of native language concepts in the use of syntactic functions of English corpora by Chinese learners of English, and points out the areas of improvement in English learning by Chinese learners of English. Finally, we design an experiment on the application of the cognitive transfer model based on the meta-learning algorithm.

IV. A. Comparative experiments with meta-learning algorithms

Similar algorithms are selected: (a1) MAML, (a2) PrototypicalNet, (a3) MAML++, (a4) ANIL, (a5) BOIL, (a6) CSS, (a7) Protocontext, (a8) Meta-Ticket, (a9) SSL-ProtoNet, (a10) SAMPTransfer, (a11) DSMNetls with (a12) the algorithms in this paper, to unfold the comparative experiments of 1-shot5-way (%) and 5-shot5-way (%) task completion on the dataset Mini-ImageNet versus the dataset tieredImageNet.

Table 1: Experimental results on the datasets Mini-ImageNet and tieredImageNet

Method	Mini-ImageNet		tieredImageNet	
	1-shot5-way(%)	5-shot5-way(%)	1-shot5-way(%)	5-shot5-way(%)
a1	-	43.77±0.47	44.83±0.50	47.56±0.44
a2	41.35±0.48	54.98±0.67	47.63±0.88	66.54±0.75
a3	46.14±0.77	74.71±0.38	41.11±0.24	59.19±0.37
a4	52.61±0.27	67.06±0.41	46.54±0.72	-
a5	47.04±0.21	73.51±0.67	41.92±0.81	65.82±0.40
a6	61.71±0.52	42.54±0.74	-	69.87±0.78
a7	72.07±0.85	41.18±0.38	-	-
a8	68.54±0.22	47.71±0.28	57.17±0.35	55.42±0.33
a9	44.84±1.22	53.86±0.37	57.67±0.52	63.69±0.37
a10	69.18±0.46	44.91±0.67	66.53±0.95	67.88±0.41
a11	54.22±1.00	43.09±0.53	-	40.42±0.83
a12	70.68±0.27	79.74±0.38	74.06±0.31	75.02±0.69

Observing Table 1, among all the compared algorithms on the dataset Mini-ImageNet with the task 5-shot5-way, (a12) the algorithm in this paper has the best performance with the highest and high accuracy of 79.74%, which is almost 5% higher than the next best (a3) MAML++, and comparing to the poorer (a7) Protocontext, it is almost 38.56%. However, when the task is 1-shot5-way, (a12) the algorithm in this paper performs only sub-optimally and does not learn enough information about the samples, which is 1.39% lower compared to the optimal (a7) Protocontext.

In the dataset tieredImageNet, the algorithm proposed in this paper shows good performance, higher than all the small-sample learning algorithms in the table. In the 1-shot 5-way task, (a12) the algorithm in this paper achieves an accuracy of 74.06% on the test set, which is much higher than the other baseline algorithms. In the 5-shot 5-way task of tieredImageNet, this paper's algorithm still outperforms all the algorithms in the baseline, achieving an accuracy of 75.02%, which is 27.46% higher than the worst (a1) MAML. As can be concluded from the more complex tieredImageNet test results, the algorithm in this paper has a significant performance advantage when dealing with complex and diverse tasks.

Excluding (a7) Protocontext algorithm and (a1) MAML algorithm which perform poorly on dataset Mini-ImageNet and dataset tieredImageNet, and (a4) ANIL algorithm, (a6) CSS algorithm and (a11) DSMNetIs algorithm which are not able to fulfill the full task. Then the comparison experiments of the seven algorithms on the datasets CIFARFS and VGG-Flower for 1-shot5-way (%) and 5-shot5-way (%) task completion are unfolded, and the comparison results of the seven algorithms are shown in Table 2.

Table 2: Experimental results on the datasets CIFARFS and VGG-Flower

Method	CIFARFS		VGG-Flower	
	1-shot5-way(%)	5-shot5-way(%)	1-shot5-way(%)	5-shot5-way(%)
a2	53.60±0.22	64.97±0.35	82.65±0.57	67.14±0.60
a3	80.56±0.71	75.27±0.61	-	73.51±0.64
a5	62.92±0.32	75.68±0.53	51.57±0.44	-
a8	66.77±0.35	85.11±0.37	-	77.48±0.57
a9	75.16±0.94	82.32±0.73	-	-
a10	78.28±0.27	69.32±0.37	62.99±0.68	-
a12	89.82±0.42	91.56±0.16	89.07±0.32	80.16±0.11

Observing Table 2, compared with the task experiments on the dataset Mini-ImageNet and the dataset tieredImageNet, the seven algorithms have improved in overall performance. Among them, (a12) this paper's algorithm achieves far superior performance than similar algorithms on all tasks on the datasets CIFARFS and VGG-Flower, with an accuracy of 91.56% on the 5-shot5-way (%) task on the dataset CIFARFS, which is 26.59% higher than that of the inferior algorithm (a2) PrototypicalNet. The experimental results in Table 2 further demonstrate the excellent classification ability of this paper's algorithm on the cognitive concept, learning ability classification task.

Combining Table 1 and Table 2, the proposed algorithm in this paper shows excellent classification performance on datasets such as Mini-ImageNet.

IV. B. Ablation Experiments on Learning Rates of Cognitive Migration Models

The reliability of the migration model proposed in this paper is verified by adjusting the learning rate, in which the meta-learning algorithm is not as sensitive as the stochastic gradient algorithm to the selection of the learning rate, and the change of the hypergradient learning rate does not affect the algorithm. In the test experiment of learning rate change, the learning rate of lr=5.0 and lr=8.00 are selected to do the test, VGG-Flower is selected as the experimental dataset, and the task is 5-shot5-way.The trend of the accuracy of the cognitive migration model with the number of iterations under different learning rates is shown in Fig. 7.

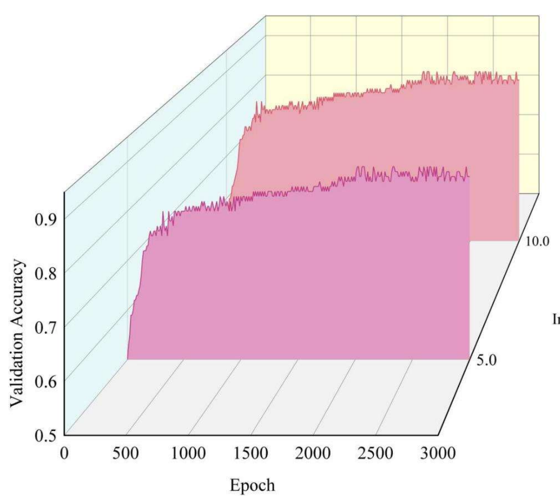


Figure 7: The variation of accuracy rate with the number of iterations

From the figure, it can be concluded that with the increase in the number of training rounds, the validation accuracies of both are significantly improved, and the model is gradually learning from the dataset. In the initial stage, the accuracy of the model on the validation set rises rapidly, the model learns from the data quickly, the rise in accuracy at lr=5.0 is slower compared to lr=10.0, but with the increase in the number of iterations, both accuracies are rising, and the rate of increase in accuracy starts to slow down gradually, the accuracy of lr=5.0 gradually catches up with that of lr=10.0 and reaches the upper limit of the model's learning ability after 2700 iterations. Although the accuracy in the validation set rises faster with a learning rate of 10.0 than with a learning rate of 5.0, both of them eventually converge to 90% after a certain iteration, demonstrating the application value of the proposed meta-learning algorithm.

IV. C. Syntactic Functional Analysis of Conducted Bodies by Different ELLs

In order to obtain the native language conceptual transfer of Chinese English language learners on English language progressives learning, so as to optimize the cognitive transfer of Chinese English language learners on English language learning. In this section, we take the syntactic functions of progressives as the object of study, and compare the variability in the syntactic functions of English progressives within Chinese ELLs. After clarifying that there is no significant difference in the use of English progressive syntactic functions within Chinese learners of English, a comparison of the differences in the distribution of syntactic functions of each progressive form between Chinese learners of English and learners of their native language in each progressive form is developed.

The syntaxes selected were (G1) main clause, (G2) gerund clause, (G3) object clause, (G4) determiner clause, (G5) running clause, (G6) subject clause, (G7) epithet clause, and (G8) homonym clause, and the forms of the progressives selected were (P1) present progressive, (P2) past progressive, (P3) present perfect progressive, (P4) past perfect progressive, (P5) auxiliary verb + progressive.

IV. C. 1) Comparison of Syntactic Functions of Chinese English Learners' Conductives

In order to more intuitively observe and compare the total frequency of each syntactic function of Chinese ELLs' internal progressives, the results of the chi-square test were conducted and are shown in Fig. 8. Except for the significant difference in the function of (G4) determiner clauses (0.01<P<0.05, which is not particularly significant), the distributions of the other syntactic functions are not significantly different from each other. In summary, it can be concluded that the syntactic functions of the internal progressives of Chinese English learners are highly homogeneous, both in terms of ordering and percentage.

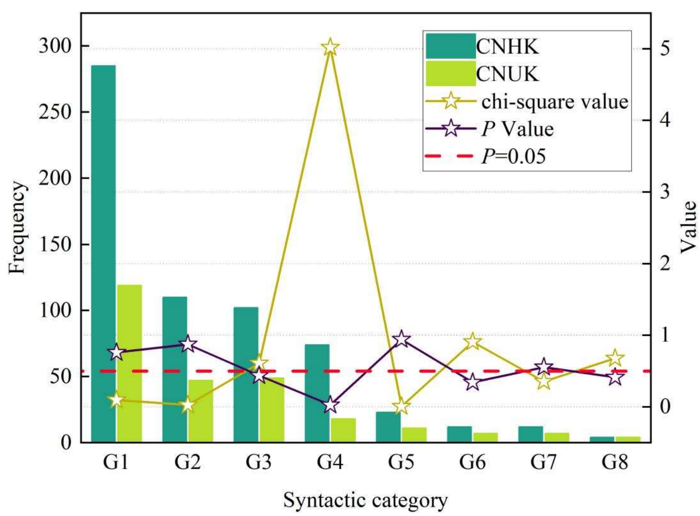


Figure 8: The chi-square test results of the overall distribution of syntactic functions

IV. C. 2) Distribution of Syntactic Functions of Different ELL Progressives

The distribution of syntactic functions of each progressive form by Chinese ELLs is shown in Table 3. Chinese ELLs used (G1) main clauses, (G2) gerund clauses, and (G3) object clauses of the progressive form more frequently, which were 366, 166, and 110, respectively. Since (G1) main clauses are in the first person, they are not uniquely discussable. Therefore, we focus on (G2) gerund clauses and (G3) object clauses in the following analysis.

Table 3: The syntactic function distribution of each progressive form

	P1	P2	P3	P4	P5	Frequency	Proportion
G1	366	20	43	2	21	452	45.98%
G2	166	9	6	0	3	184	18.72%
G3	110	29	7	2	13	161	16.38%
G4	75	3	6	0	15	99	10.07%
G5	33	3	0	0	0	36	3.66%
G6	19	0	0	0	0	19	1.93%
G7	14	2	2	0	3	21	2.14%
G8	5	2	2	0	2	11	1.12%
Total	788	68	66	4	57	983	100%

Differences and similarities between Chinese learners of English and learners of native English in carrying out somatic syntactic functions are shown in Figure 9.

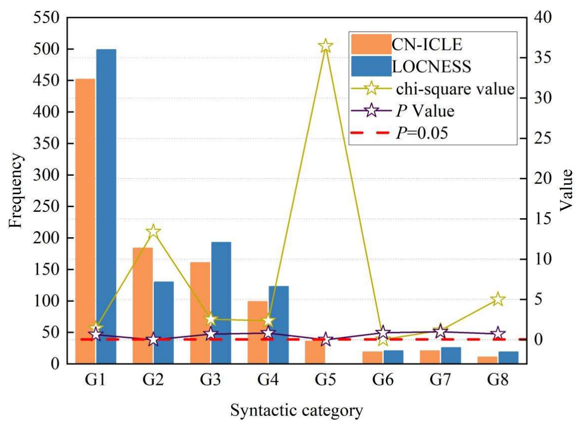


Figure 9: The test results of Chinese learners and English bathing learners

As can be seen at a glance in Figure 9, there is a significant difference in both (G2) gerund clause function and (G5) running clauses between Chinese English learners and native English learners of the corpora (P=0.00<0.001), but there is no significant difference in (G3) object clauses (P=0.712>0.05), and the percentage of (G2) gerund clause function is significantly higher for Chinese English learners than native English learners. In particular, the difference in (G5) running clauses is even more obvious, as there are no (G5) running clauses in the clauses where the English native speakers' progressives are located, whereas nearly 5% of the clauses where the Chinese learners' progressives are located in the output of the Chinese learners of English are special Chinese sentence forms such as (G5) running clauses.

To summarize, in terms of the syntactic functional use of the progressive form, there is also within-group homogeneity within Chinese ELLs and heterogeneity between Chinese ELLs and native English learners. In addition, Chinese ELLs' use of syntactic functions of English progressives is similar to that of Chinese syntactic functions, suggesting that Chinese ELLs have a more obvious transfer of native language concepts in the use of syntactic functions of English progressives. Under the influence of native language conceptual transfer, Chinese ELLs' use of syntactic functions of English progressives deviates from its original track, and at this time, native language conceptual transfer is a kind of negative transfer.

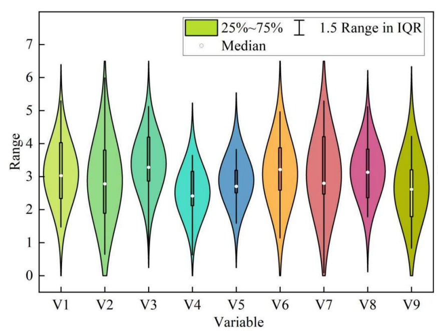
IV. D. Tests of Reading Comprehension and Data Analysis

In order to explore the feasibility of the cognitive transfer strategy designed in this paper in actual English learning, this section chooses two classes of English majors in College C with comparable English proficiency as the experimental subjects. Each of the two classes has 20 students, and the class with the cognitive transfer model proposed in this paper to assist teaching and learning is the experimental class, while the class with the normal teaching and learning mode is the control class. The pairing of the experimental class and the control class before the experiment is shown in Table 4.

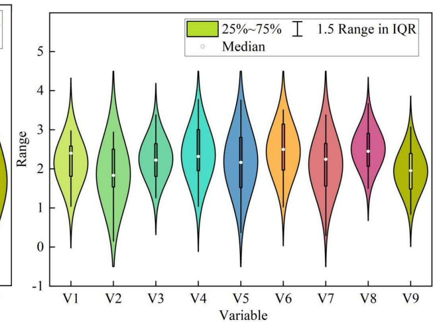
Table 4: The pairing situation before the experiment

Pairing (M±SD)	Pairing 1	82.64±3.77
	Pairing 2	82.29±3.64
Difference (Pairing 1- Pairing 2)		0.35
t		0.795
P		0.432
Evaluate the mean difference		0.35
The difference is 95% CI		-0.538~1.236
df		43
Difference standard deviation		2.881
Cohen's d value		0.122

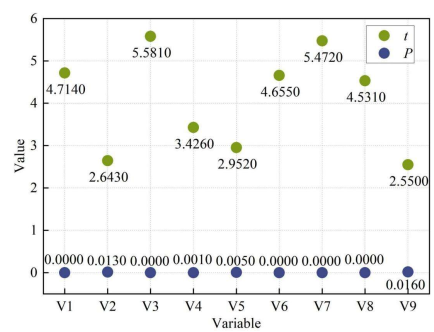
From the above, it can be seen that when the matched t-test was used to study the bias of the experimental data, there was a total of 1 set of matched data, which did not show any difference (P=0.432>0.05), while the value of Cohen's d for the matched samples t-test was 0.122.



(a) The performance of the experimental class on each variable



(b) The performance of the control class on each variable



(c) The results of the significant difference test

Figure 10: Evaluation and comparison of the learning process effect

According to the process of learning activities with the corresponding teaching behaviors, the learning effects presented on the whole reading comprehension test were evaluated in the experiment with respect to the variables of (V1) activation, (V2) prediction, (V3) analysis, (V4) validation, (V5) inference, (V6) generalization, (V7) transfer, (V8) innovation, and (V9) assessment out of 10 points. Figure 10(a) shows the learning performance of the experimental class as a whole on each variable after the experiment, Figure 10(b) shows the learning performance of the control class as a whole on each variable after the experiment, and Figure 10(c) shows the results of the significance test of the difference between the experimental class and the control class on the nine assessment variables after the experiment. The performance of the experimental class on each variable was higher than that of the control class as a whole, and the mean score of the ratings obtained by the experimental class on each variable was 2.5 and above, while the mean score of the ratings obtained by the control class was the highest for the activation of the variable:(V1) at 2.15. And the mean scores of the ratings obtained by the experimental class and the control class on the nine variables showed significant differences ($P<0.05$). Under the guidance of the cognitive transfer strategy designed in this paper, students are able to effectively carry out cognitive transfer of learning and promote their English language learning effectiveness.

V. Conclusion

The research conclusions of this paper are as follows:

(1) By constructing a cognitive migration model based on meta-learning algorithms and proposing a problem-solving process based on migration, a framework for the application of cognitive migration in college English teaching is formed. Combining learners' metacognition, learning transfer ability and teaching tools, we promote the development of students' metacognitive transfer ability and cultivate foreign language talents who meet the needs of the new era.

(2) Exploring the differences in the use of syntactic functions on English progressives between Chinese learners of English and learners of native English, it is found that Chinese learners of English have a more obvious transfer of concepts from their mother tongue in the learning of English progressives. Chinese learners of English use gerund clauses and running clauses more frequently, which is a significant manifestation of the transfer of native language learning methods, a kind of negative transfer. Therefore, in the teaching of college English, teachers should pay attention to students' cognitive transfer and try to help students overcome the influence of negative transfer.

(3) The designed meta-learning algorithm has a higher accuracy rate of up to 91.56% for multiple dataset task completion compared with similar algorithms. The cognitive migration model based on the meta-learning algorithm has a convergence rate of up to 90% at different learning rates. In practical application, the experimental class tutored in teaching and learning using the cognitive migration model based on the meta-learning algorithm showed significant differences ($P<0.05$) in all nine evaluation variables from the control class using the ordinary teaching model.

References

[1] Rao, P. S. (2019). The role of English as a global language. Research journal of English, 4(1), 65-79.

[2] Melitz, J. (2016). English as a global language. In The Palgrave handbook of economics and language (pp. 583-615). London: Palgrave Macmillan UK.

[3] Denizer, E. N. (2017). Does mother tongue interfere in second language learning?. Journal of Foreign Language Education and Technology, 2(1), 39-54.

[4] Sharma, S. (2015). Mother tongue influence on English language learning. Scholarly Research Journal For Humanity Science & English Language, 2(6), 2165-2169.

[5] Sala, G., Aksayli, N. D., Tatlidil, K. S., Tatsumi, T., Gondo, Y., & Gobet, F. (2019). Near and far transfer in cognitive training: A second-order meta-analysis. Collabra: Psychology, 5(1), 18.

[6] Peng, M. Y. P., Feng, Y., Zhao, X., & Chong, W. (2021). Use of knowledge transfer theory to improve learning outcomes of cognitive and non-cognitive skills of university students: Evidence from Taiwan. Frontiers in Psychology, 12, 583722.

[7] Huang, Y. (2023). Nurturing Foreign Language Talents of the New Era with a New Academic Style. International Journal of New Developments in Education, 5(14).

[8] James, M. A. (2018). Teaching for transfer of second language learning. Language Teaching, 51(3), 330-348.

[9] Hill, C., Khoo, S., & Hsieh, Y. C. (2020). An investigation into the learning transfer of English for specific Academic Purposes (ESAP) writing skills of students in Singapore. Journal of English for Academic Purposes, 48, 100908.

[10] Penner-Williams, J., Díaz, E. I., & Worthen, D. G. (2017). PLCs: Key PD component in learning transfer for teachers of English learners. Teaching and Teacher Education, 65, 215-229.

[11] Muthmainnah, M., Cardoso, L., Marzuki, A. G., & Al Yakin, A. (2025). A new innovative metaverse ecosystem: VR-based human interaction enhances EFL learners' transferable skills. Discover Sustainability, 6(1), 156.

[12] Nan, C. (2018). Implications of interrelationship among four language skills for high school English teaching. Journal of Language Teaching and Research, 9(2), 418-423.

[13] Nsengimana, I., Niyibizi, E., & Ngabonziza, J. D. D. A. (2024). The Impact of Language Transfers on Learners Writing Skills in English Learning Among Students in Mahama Refugee Camp, Rwanda. African Journal of Empirical Research, 5(3), 605-613.

[14] Collins-Nelsen, R., Koziarz, F., Levinson, B., Allard, E., Verkoeyen, S., & Raha, S. (2022). Social context and transferable skill development in experiential learning. Innovations in Education and Teaching International, 59(4), 421-430.

[15] Cummins, J. (2017). Teaching for transfer in multilingual school contexts. Bilingual and multilingual education, 3, 103-115.

[16] Heng, L., & Yeh, H. C. (2024). How can a task-based project enhance students' transferable skills? An investigation. Educational Research, 66(2), 139-154.

[17] Kato, M. (2018). Exploring the Transfer Relationship of Summarizing Skills in L1 and L2. English Language Teaching, 11(10), 75-87.

[18] Hajian, S. (2019). Transfer of learning and teaching: A review of transfer theories and effective instructional practices. IAFOR Journal of education, 7(1), 93-111.