

Optimizing Student-Personalized English Translation Training Systems in Low-Resource Settings Using Meta-Learning

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ABSTRACT Addressing core challenges in English translation training under low-resource conditions, including resource scarcity and insufficient personalized adaptation, this study proposes a student-tailored optimization framework based on Meta-Learning. The approach is particularly applicable to specialized domains where high-quality parallel corpora are limited and efficient knowledge transfer is essential. In resource-constrained environments, conventional training systems struggle to capture individual learning characteristics and provide effective personalized services due to inadequate data availability. By exploiting the “learning to learn” capability of Meta-Learning, the proposed framework transfers cross-task knowledge to compensate for limited resources while improving adaptation efficiency. Integrating personalized learning theory with translation pedagogy, the study develops a system architecture featuring multidimensional translation competency assessment, adaptive training path generation, precise error diagnosis, and personalized resource recommendation. The optimized system rapidly adapts to students’ knowledge bases, preferences, and competency gaps without relying on large-scale datasets, thereby delivering customized translation training in low-resource settings. Beyond its educational applications, the proposed framework demonstrates the potential of data-efficient intelligent learning strategies for information processing and computational modeling in complex engineering systems, offering methodological insights for intelligent signal analysis and resource-constrained electromagnetic information processing scenarios.

INDEX TERMS meta-learning, low-resource settings, personalized learning system, intelligent signal processing, English translation training

I. INTRODUCTION

RESEARCH BACKGROUND

META-LEARNING, as a machine learning paradigm that “learns to learn,” excels at rapidly adapting to new tasks or individuals using minimal samples. By acquiring common knowledge across multiple tasks, it develops general learning capabilities that enable swift adaptation to specialized terminology, such as those found in the industry, without requiring large-scale, domain-specific data [1-4]. This characteristic aligns perfectly with the demands of personalized English translation training in low-resource scenarios: Meta-Learning compensates for insufficient data from individual students by learning cross-student, cross-task common knowledge. Leveraging its rapid adaptation capability, it can accurately capture each student’s learning characteristics, error patterns, and skill gaps, enabling personalized training content delivery and real-time feedback. Integrating Meta-Learning into low-resource English

translation training systems holds promise for overcoming technical limitations of traditional systems. This integration offers efficient and precise personalized translation instruction solutions for resource-constrained educational settings, particularly those focused on specialized vocational fields, which demand highly accurate and rapidly adaptable domain expertise [5,6].

CURRENT STATE OF META-LEARNING TECHNOLOGY RESEARCH

Since its inception in the 1990s, meta-learning has evolved into four mainstream approaches: optimization-based (e.g., MAML, Reptile), metric-based (e.g., Prototypical Networks, Matching Networks), model-based (e.g., Memory-Augmented Neural Networks), and reinforcement learning-based (e.g., Meta-Policy Gradient) [7-10]. Optimization-based meta-learning enables models to adapt to new tasks with minimal gradient updates over sparse samples by

learning universal initialization parameters, demonstrating strong performance in few-shot classification and regression tasks [11]. Metric-based meta-learning achieves rapid classification and recognition of novel samples by constructing task-specific distance metric spaces, making it suitable for scenarios with high-dimensional data features [12].

Existing personalized English translation training systems primarily fall into three categories: rule-based systems, traditional machine learning-based systems, and deep learning-based systems. Rule-based systems provide translation guidance through predefined rules and error databases, but their rule-base construction is costly and inflexible, making it difficult to adapt to individual students' learning characteristics [13-15]. Systems based on traditional machine learning analyze student learning data (e.g., translation assignments, test scores) to identify learning gaps and recommend resources. However, these systems rely on large-scale labeled data, limiting their performance in low-resource scenarios [16].

RESEARCH CONTENT AND METHODS

RESEARCH CONTENT

This study focuses on optimizing personalized English translation training systems for students in low-resource scenarios. Specific research content includes:

(1) Analysis of English translation training needs in low-resource settings.

Through questionnaires and interviews, we surveyed students and teachers in low-resource regions regarding their English translation training requirements, including learning resource needs, personalized guidance demands, and assessment feedback expectations. We analyzed common challenges and skill gaps in English translation learning to define core functional requirements and technical metrics for the system.

(2) Design of the overall system architecture based on Meta-Learning.

Based on the analysis results, design the system's overall architecture, including data layer, core algorithm layer, functional module layer, and application layer. Determine the specific meta-learning algorithm selection (combining optimization-based meta-learning with metric-based meta-learning) to construct a personalized learning framework.

(3) Core Module Development and Optimization.

This includes:

1 Data processing module: Design data collection and preprocessing solutions for low-resource scenarios, expanding sample size through data augmentation and cross-task data sharing.

2 Meta-learning model training module: Optimizing model initialization parameters using the MAML algorithm and constructing a translation capability evaluation metric space with Prototypical Networks;

3 Personalized recommendation module: Delivering targeted translation training content, learning resources, and error correction guidance based on meta-learning model outputs;

4 Multi-dimensional evaluation module: Establishing a translation capability assessment system covering lexical, syntactic, stylistic, and semantic dimensions, integrating formative and summative evaluations.

(4) System Development and Testing.

Developed a personalized English translation training system using Python, Django, Vue.js, and other technologies. Conducted system testing in three low-resource secondary schools (involving 240 students and 12 teachers) to validate system stability, usability, and personalized service effectiveness.

(5) Teaching Experiment and Effectiveness Validation.

Design a teaching experiment dividing participants into an experimental group (using the optimized system) and a control group (using a traditional translation training system) for a 16-week intervention. Collect data through translation proficiency tests, questionnaires, and teacher interviews to compare translation performance, learning engagement, and skill improvement between groups, validating the system's pedagogical efficacy.

RESEARCH METHODS

(1) Literature Review Method.

Conduct a systematic review of relevant literature in the fields of low-resource English translation instruction, Meta-Learning technology, and personalized learning systems. Understand the current state and development trends of domestic and international research to provide a basis for constructing the theoretical framework and designing the technical solution for this study.

(2) Needs Assessment Method.

Employing questionnaires and semi-structured interviews, we surveyed students and teachers in low-resource secondary schools. Student questionnaires assessed their English translation fundamentals, learning needs, common challenges, and expectations for the training system. Teacher questionnaires gathered insights on teaching pain points, demand for personalized instruction, and evaluation criteria. Interviews with teaching administrators examined school hardware conditions and resource constraints to ensure system design aligns with practical application scenarios.

(3) System Design Method.

Following the development process of "needs analysis → overall architecture design → module design → development and testing," the system was divided into core modules—data processing, meta-learning models, personalized recommendations, and multidimensional assessment—using a modular design approach. The functions, interfaces, and technical implementation plans for each module were defined to ensure compatibility and scalability between modules.

(4) Experimental Research Method.

Three secondary schools in low-resource settings were selected, with students randomly assigned to an experimental group (120 students) and a control group (120

students). The experimental group used a Meta-Learning-based personalized translation training system, while the control group used a traditional translation training system. Irrelevant variables such as teaching content, duration, and instructors were controlled, with only the training system varying. Data was collected through translation proficiency tests (pre-test, mid-test, post-test) and learning behavior log analysis to compare learning outcomes between groups.

(5) Data Analysis Methodology.

A combined quantitative and qualitative approach was employed to process experimental data. For quantitative analysis, SPSS statistical software conducted independent samples t-tests on variables including translation scores, learning duration, and training completion rates across both groups to validate statistical significance. Qualitative analysis involved coding and analyzing student translation assignments, questionnaire feedback, and teacher interview records to identify changes in translation proficiency and learning engagement.

II. THEORETICAL FOUNDATIONS

THEORIES RELATED TO PERSONALIZED LEARNING

Mastery Learning Theory, proposed by American educator Benjamin Bloom in the 1960s, centers on the principle that learning disparities among students primarily stem from differences in learning time and methods, rather than variations in intellectual capacity. By providing appropriate learning conditions—including personalized content, sufficient time, and targeted feedback—the vast majority of students (over 90%) can achieve predetermined learning objectives [17-20]. This theory emphasizes a student-centered approach, advocating for the adjustment of teaching strategies based on students' learning progress and mastery levels to achieve the educational goal of "teaching according to individual aptitude."

Constructivist learning theory originated from Piaget's cognitive development theory and was further developed and refined by scholars such as Vygotsky and Bruner, forming a learning theoretical framework centered on "active construction, contextual interaction, and meaning generation" [21,22]. This theory posits that learning is not a passive process of receiving external information, but rather an active process where learners construct knowledge meaning through interaction with their environment and others within specific sociocultural contexts. Learners' knowledge systems gradually form through autonomous inquiry, collaborative exchange, and reflective summarization based on personal experience. Authentic problem contexts and opportunities for independent exploration serve as critical vehicles for knowledge construction. English translation proficiency is fundamentally a practical language application skill. Its development inherently requires authentic translation contexts and active reflective practice. Traditional English translation training primarily focuses on isolated sentence translation exercises, lacking authentic contextual support. This results in students mastering basic translation rules yet

struggling to apply them flexibly in real-world scenarios, leading to a "paper tiger" phenomenon [23]. In low-resource settings, this issue becomes more pronounced due to the scarcity of authentic translation practice opportunities and cross-cultural communication contexts.

META-LEARNING RELATED THEORIES

CORE CONCEPTS AND ESSENCE OF META-LEARNING

Meta-Learning, also known as "Learning to Learn," represents a significant research direction in machine learning. Its core objective is to enable models to acquire the ability to rapidly adapt to new tasks or environments by learning common knowledge and experience across multiple tasks [24]. Unlike traditional machine learning, which focuses on training models for individual tasks, meta-learning trains the "learning strategy" itself. By learning from a large number of related tasks, it distills universal learning capabilities, enabling models to converge quickly and achieve good performance with only a small number of samples when faced with new tasks.

At its core, meta-learning represents cross-task knowledge transfer and generalization, with its fundamental logic summarized as "learning prior knowledge followed by rapid adaptation to new tasks." Here, "prior knowledge" refers to common patterns and underlying features shared across multiple related tasks. For instance, different students exhibit common types of errors in English translation (such as incorrect word combinations, grammatical structure errors, or loss of meaning), and various translation tasks share common requirements for linguistic accuracy, fluency, and cultural adaptation [25]. By learning these shared patterns, Meta-Learning constructs universal model initialization parameters or feature extraction frameworks. When encountering new individual students or translation tasks, it achieves rapid adaptation through fine-tuning with minimal samples, enabling personalized translation guidance and competency assessment, please refer to Table 1 for details.

In low-resource scenarios, this inherent characteristic of Meta-Learning offers irreplaceable advantages. Traditional machine learning models require large-scale student learning data (e.g., translation practice records, error feedback, competency assessment results) to accurately model student learning states. However, in low-resource settings, sample data per student is often extremely limited, leading to poor model generalization and insufficient personalized accuracy [26]. Meta-learning overcomes this limitation by learning cross-student and cross-task common knowledge. It rapidly captures individual student differences with minimal data, providing a viable technical pathway for personalized English translation training in resource-constrained environments.

MAINSTREAM META-LEARNING METHODS AND CLASSIFICATION

Since its inception, Meta-Learning has evolved over decades into four major methodological frameworks. These ap-

TABLE 1. Core Characteristics and Advantages of Meta-Learning in Low-Resource English Translation Training

Aspect	Detailed Description
Definition & Core Goal	Meta-Learning (Learning to Learn) is a key research direction in machine learning. Its core goal is to enable models to acquire the ability to quickly adapt to new tasks or environments by learning common knowledge and experience from multiple tasks. Unlike traditional machine learning that focuses on training models for single tasks, Meta-Learning trains "learning strategies" themselves.
Essential Logic	It is essentially cross-task knowledge transfer and generalization, summarized as "prior knowledge learning → rapid adaptation to new tasks". "Prior knowledge" refers to the common laws and underlying features among multiple related tasks (e.g., common translation error types of students, shared requirements for translation quality across tasks).
Working Mechanism	By learning such common knowledge, Meta-Learning constructs general model initialization parameters or feature extraction frameworks. When facing new students or translation tasks, it can achieve rapid adaptation through minor fine-tuning with a small amount of samples, enabling personalized translation guidance and competence evaluation.
Advantages in Low-Resource Scenarios	Traditional machine learning models require large-scale student learning data to accurately model learning status, which is scarce in low-resource scenarios, leading to poor generalization and insufficient personalization. Meta-Learning makes up for the lack of individual student samples through cross-student and cross-task common knowledge learning, capturing individual differences with limited data and providing a feasible technical path for personalized English translation training.

proaches differ in technical principles, applicable scenarios, and performance metrics, as detailed below:

(1) Optimization-Based Meta-Learning

Optimization-based meta-learning is one of the most widely applied meta-learning approaches. Its core idea involves learning a universal model initialization parameter during a meta-training phase, enabling the model to rapidly adapt to new tasks with minimal gradient updates (i.e., "fine-tuning") [27]. The method's core lies in optimizing the model's initialization parameters to position them in a "new-task-sensitive" region, enabling rapid convergence to optimal parameters with minimal samples.

Typical optimization-based meta-learning algorithms include Model-Agnostic Meta-Learning (MAML), Reptile, and First-Order MAML. MAML, proposed by Finn et al. in 2017, employs a meta-training process comprising an inner loop and an outer loop: the inner loop performs gradient descent on a small support set of samples for each task to update model parameters; the outer loop updates initial parameters based on the query set loss across multiple tasks, optimizing the model's generalization performance across diverse tasks [28]. Reptile is a simplified version of MAML that optimizes initial parameters by averaging parameter update trajectories across multiple tasks. It features lower computational complexity, more stable training, and is suitable for scenarios with limited data [29].

Optimization-based meta-learning methods exhibit strong versatility, applicable to various machine learning tasks (classification, regression, generation, etc.), particularly excelling under few-shot conditions. In personalized English translation training systems, this approach can learn universal feature representations of student translation abilities. By meta-training on multiple students' learning data, it obtains a universal initialized model. When encountering a new student, only a small amount of translation practice data is needed for rapid adaptation, enabling precise identification of their skill gaps and error patterns [30].

(2) Metric-Based Meta-Learning

The core idea of metric-based meta-learning is to construct a task-specific distance metric space. By calculating the similarity between new samples and those in the support set, it enables classification or prediction of new samples. This approach does not rely on complex parameter fine-tuning but focuses on learning effective feature representations and similarity metric functions. This ensures that similar samples cluster together in the metric space while dissimilar samples remain distant.

Typical metric-based meta-learning algorithms include Prototypical Networks, Matching Networks, and Relation Networks. Prototypical Networks calculate the average feature values ("prototypes") of support set samples per class, then assign new samples to the closest prototype category—a simple, efficient approach suitable for classification tasks. Matching Networks employ attention mechanisms to compute similarity weights between new samples and each support sample, then perform weighted summation to generate predictions. This approach captures fine-grained differences between samples.

Metric-based meta-learning methods demonstrate significant advantages in scenarios with high feature dimensions and sparse data, particularly for classification and recognition tasks. In English translation training systems, this approach can be applied to tasks like error type identification and translation proficiency assessment. For instance, meta-training constructs prototype features for different error types (e.g., lexical, syntactic, semantic errors). When a new student submits a translation exercise, the system calculates similarity between the text features and each error prototype, rapidly pinpointing the core error type.

(3) Reinforcement Learning-Based Meta-Learning

Reinforcement learning-based meta-learning transforms meta-learning problems into reinforcement learning problems by training a meta-policy to rapidly learn optimal strategies across diverse task environments. Its core lies in leveraging reinforcement learning's reward mechanism to guide the meta-policy in learning cross-task generalizable

decision rules, making it suitable for sequential decision-making and dynamic environments.

Typical reinforcement learning-based meta-learning algorithms include Meta-Policy Gradient and Trust Region Meta-Learning. Meta-Policy Gradient trains policy networks across multiple tasks, enabling rapid adaptation to new reward functions—ideal for scenarios with significant reward mechanism variations. Trust Region Meta-Learning introduces trust region constraints to ensure stability in policy updates, preventing performance degradation caused by task variations.

Reinforcement learning-based meta-learning methods excel in tasks requiring dynamic policy adjustments. In English translation training systems, this approach can dynamically optimize personalized learning paths. By analyzing real-time student feedback—such as exercise accuracy, study duration, and interest preferences—it adjusts training tasks and resource allocation strategies to maximize learning outcomes. For instance, if a student demonstrates high interest and accuracy in a specific translation task category, the system can increase the proportion of similar tasks through reinforcement learning mechanisms. Conversely, if a student consistently struggles with a particular task type despite repeated attempts, the system can promptly adjust task difficulty or switch training approaches.

APPLICATION CHARACTERISTICS OF META-LEARNING IN EDUCATION

Meta-Learning's core characteristics align closely with personalized learning demands in education, exhibiting the following distinct features in educational settings:

Ablation experiments were conducted to verify the effectiveness of the transfer mechanism: Removing the general technical document source task transfer resulted in a 13.2% system performance decrease; Removing the general news source task transfer led to a 6.5% performance decrease. This confirms that cross-task knowledge transfer significantly enhances the system's low-resource adaptation capability

(1) Rapid Adaptability with Small Samples

By learning cross-task commonalities, Meta-Learning rapidly adapts to new tasks or individuals using minimal samples. This property perfectly addresses the scarcity of individual student data in resource-constrained educational environments. In English translation training, each student's learning data (e.g., translation exercises, error feedback) is often extremely limited. Traditional machine learning models struggle to accurately model a student's learning state based on such sparse data. Meta-Learning, however, learns common features across multiple students (e.g., frequent error types, learning progression patterns) to rapidly adapt to new learners. It can identify a new student's skill gaps and learning preferences with just dozens of translation examples.

(2) Cross-Task Knowledge Transfer

Meta-Learning extracts common knowledge across related tasks and transfers it to new tasks, enhancing learning efficiency for novel tasks. In English translation training, common knowledge exists across different translation tasks (e.g., word translation, sentence translation, passage translation) and text types (e.g., scientific texts, literary texts, business texts)—such as principles of translation accuracy, requirements for semantic coherence, and grammatical norms. Meta-Learning can learn this shared knowledge and transfer it to specific translation tasks, helping students rapidly master core techniques for various translation tasks and improve learning efficiency.

(3) Dynamic Adaptive Capabilities

Meta-Learning models dynamically adjust parameters or strategies in real-time based on feedback from new tasks. During English translation training, learners' states evolve dynamically (e.g., skill progression, shifting interests, changing weaknesses). Meta-Learning-based systems capture these changes instantly, dynamically adjusting training content, difficulty levels, and pacing. For instance, when a student's vocabulary translation proficiency significantly improves, the system can automatically increase the proportion of sentence and passage translation exercises. When a student's interest in translating a particular text type wanes, the system can adjust training scenarios or resource formats to maintain learning motivation.

(4) Personalized Modeling Capability

By precisely capturing individual differences, Meta-Learning constructs personalized models for each learner, providing tailored learning support. Unlike traditional recommendation algorithms based on group characteristics, Meta-Learning can extract unique learning traits (such as learning pace, error patterns, and cognitive preferences) from minimal individual data, enabling more precise personalized recommendations and feedback. For instance, for students who prefer visual learning, the system can recommend translation resources combining text and images; for students with slower learning paces, the system can appropriately reduce task difficulty gradients and extend practice time.

Two source tasks highly relevant to textile translation were selected for knowledge transfer:

General Technical Document Translation Task (mechanical and chemical fields): Transfers common knowledge of technical text translation, including syntactic frameworks (e.g., passive voice application), professional terminology collocation rules, and error type patterns;

General News Translation Task: Provides basic language ability support, including core vocabulary collocation, basic syntactic structure, and learning progress adaptation rules.

The transferred knowledge focuses on three types of common features:

(1) Technical text syntactic frameworks;

(2) Translation error type patterns (e.g., vocabulary collocation errors, semantic loss);

(3) Learning progress adaptation rules (e.g., skill advancement paths), See Table 2 for details.

III. REQUIREMENTS ANALYSIS FOR A STUDENT-PERSONALIZED ENGLISH TRANSLATION TRAINING SYSTEM IN LOW-RESOURCE SETTINGS

RESEARCH METHODS AND TOOLS

This study employs a hybrid research approach combining “questionnaire surveys + semi-structured interviews + classroom observations” to ensure comprehensive and authentic data collection.

(1) Questionnaire Survey:

Three distinct questionnaires were designed for students, teachers, and teaching administrators. The student questionnaire encompassed four dimensions (self-assessment of translation ability, learning preferences, experience with existing tools, and personalized needs), comprising 28 questions: 18 single-choice, 6 multiple-choice, and 4 Likert 5-point scale items. The faculty questionnaire covered five dimensions (current teaching practices, resource needs, challenges in student assessment, technological tool requirements, and system functionality expectations), comprising 32 questions. The administrative questionnaire focused on school hardware conditions, resource allocation, and technical support capabilities, totaling 15 questions. Surveys were distributed via both an online platform (Quanxunxing) and paper copies to ensure accessibility in low-resource areas. This study was approved by the Ethics Committee of SIAS University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

(2) Semi-structured interviews:

An interview outline was designed to conduct one-on-one interviews with 20 students (across different grades and proficiency levels), 12 teachers, and 6 teaching administrators. Discussions centered on core pain points, such as students' translation learning difficulties and specific expectations for personalized guidance; teachers' challenges in diagnosing student errors and implementing personalized instruction; and administrators' hardware and technical requirements for system deployment. Each interview lasted 15-25 minutes, fully recorded and transcribed into written materials.

(3) Classroom Observation:

Observed 12 English translation lessons (6 junior high, 6 senior high) to document teaching models, resource usage, teacher-student interactions, and student performance, analyzing limitations of existing teaching approaches. Observations utilized a structured observation form covering 10 dimensions: teaching objectives, content, methods, student engagement, feedback approaches, etc.

The research unfolded in three phases:

Phase 1 (Preliminary Research):

Involved 30 students and 3 teachers from one secondary school to validate questionnaire and interview guide validity. Ambiguous or illogical phrasing was refined to ensure research tool effectiveness.

Phase 2 (Main Survey):

Simultaneously conducted questionnaires, interviews, and classroom observations across 6 secondary schools over 4 weeks. A total of 528 questionnaires were distributed, with 498 valid responses collected (94.3% valid response rate), including 462 student questionnaires (96.2% valid return rate), 30 teacher questionnaires (83.3% valid return rate), and 6 administrator questionnaires (50.0% valid return rate). A total of 38 interviews and 12 classroom observations were completed.

Phase Three (Data Organization):

Questionnaire data was coded and entered, with statistical analysis conducted using SPSS 26.0. Interview recordings and classroom observation notes were transcribed and coded to extract core insights.

ANALYSIS OF LOW-RESOURCE SCENARIO CHARACTERISTICS

Definition of Low-Resource Settings: Based on field research, low-resource scenarios are quantitatively defined as:

- (1) Average number of translation samples per student ≤ 50 ;
- (2) School available teaching resource library scale $\leq 10,000$ entries;
- (3) Network bandwidth $\leq 10\text{Mbps}$;
- (4) Terminal device memory $\leq 4\text{GB}$, consistent with the actual conditions of surveyed low-resource area schools.

HARDWARE RESOURCE CONSTRAINTS

Research findings indicate that hardware constraints in low-resource scenarios manifest primarily in three aspects:

First, terminal devices are insufficiently configured and outdated. Only 2 of the 6 middle schools have computer labs, with the number of computers only sufficient for 30% of students to use simultaneously. Device configurations are generally low (CPU Intel Core i3 or below, memory 4GB or below), making it difficult to run complex translation training software.

Second, limited network conditions: only 4 schools possess basic campus networks with bandwidth $\leq 10\text{Mbps}$. In rural areas, home internet coverage among students is merely 45%, highlighting the need for offline functionality.

Third, scarcity of multimedia teaching equipment: only 30% of classrooms are equipped with interactive whiteboards, while most rely on traditional projectors, making it difficult to support the display of multimodal learning resources and interactive teaching.

SCARCITY OF TEACHING RESOURCES

Teaching resource scarcity in low-resource settings manifests as dual deficiencies in both “quality” and “quantity”:

First, limited resource quantity—teachers primarily rely on textbook exercises and sparse free online courseware for translation instruction, with insufficient high-quality materials (e.g., authentic discourse, multimodal resources). 83.3%

TABLE 2. Mainstream Approaches and Classification of Meta-Learning

Meta-Learning Method Category	Core Idea	Technical Features	Applicable Scenarios	Application in English Translation Training Systems
Optimization-Based Meta-Learning	Learn universal model initialization parameters during meta-training, enabling the model to quickly adapt to new tasks with only a few gradient updates (i.e., "fine-tuning").	MAML's meta-training process consists of inner and outer loops: the inner loop updates model parameters via gradient descent using a small number of support set samples for each task; the outer loop updates initial parameters based on the loss of query set samples across multiple tasks to optimize generalization performance. Reptile simplifies MAML by averaging parameter update trajectories across tasks, offering lower computational complexity and more stable training.	Highly versatile for various machine learning tasks (classification, regression, generation, etc.), especially excelling in few-shot scenarios.	Learn universal feature representations of students' translation competence. Conduct meta-training on learning data from multiple students to obtain a general initialized model. When facing new students, quickly adapt with only a small amount of translation practice data to accurately identify their competence gaps and error types.
Metric-Based Meta-Learning	Construct a task-specific distance metric space to classify or predict new samples by calculating their similarity with samples in the support set.	Prototypical Networks compute the average of support set sample features for each category as the "prototype," then classify new samples into the category with the closest prototype. Matching Networks use attention mechanisms to calculate similarity weights between new samples and each support set sample, generating predictions through weighted summation.	Distinct advantages in scenarios with high-dimensional features and small sample sizes, particularly suitable for classification and recognition tasks.	Applied in translation error type identification and translation proficiency assessment. Build prototype features for different error types (e.g., vocabulary errors, grammar errors, semantic errors) through meta-training. After students submit translation exercises, the system calculates the similarity between the translation text features and each error type prototype to quickly locate core error types.
Reinforcement Learning-Based Meta-Learning	Transform meta-learning problems into reinforcement learning problems by training a meta-policy that can quickly learn optimal strategies in different task environments.	Meta-Policy Gradient trains policy networks across multiple tasks to enable rapid adaptation to new tasks' reward functions. Trust Region Meta-Learning introduces trust region constraints to ensure stable policy updates and avoid performance degradation due to task differences.	Advantageous in tasks requiring dynamic strategy adjustment.	Dynamically optimize personalized learning paths. Adjust training tasks and resource recommendation strategies based on students' real-time learning feedback (e.g., practice accuracy, learning duration, interest preferences) to maximize learning effectiveness. For example, if a student shows high interest and accuracy in a certain type of translation task, the system increases the proportion of similar tasks via reinforcement learning mechanisms; if a student struggles repeatedly with a task, it promptly adjusts task difficulty or switches training methods.

of teachers report “lack of targeted translation training material repositories”;

Second, resources exhibit poor adaptability, with existing materials predominantly generic and failing to account for students’ foundational proficiency levels in low-resource areas (e.g., limited vocabulary, weak grammar). 66.7% of teachers believe “existing resources are either too difficult or too easy, failing to match students’ actual proficiency levels.”

Third, resource formats are overly monotonous, dominated by text-based materials, with audio, video, and interactive resources accounting for less than 15% of the total, unable to meet the needs of students with diverse learning styles.

INSUFFICIENT STUDENT DATA SAMPLES

Translation learning data for individual students in low-resource settings is severely lacking:

First, data types are limited, with schools only recording final translation test scores and lacking process-based data (e.g., daily practice errors, learning trajectories, thought processes).

Second, sample sizes are small, with fewer than 50 standardized translation practice entries per student per semester, insufficient to support personalized modeling using traditional machine learning models.

Third, data sharing is challenging. There is no unified storage or sharing mechanism for student data across different classes or schools, preventing the formation of scalable datasets.

Supplementary Textile Domain Corpus Details: The specialized parallel corpus used in this study contains 8,500 sets of parallel sentences (English original-Chinese translation), covering 6 sub-domains including textile materials,

production processes, and product descriptions. The meta-training set accounts for 70% (5,950 sets), the meta-test set accounts for 30% (2,550 sets), and 500 sets are used for model validation.

SYSTEM FUNCTIONALITY AND TECHNICAL REQUIREMENTS ANALYSIS

Based on the research findings, the system must fulfill four core functional requirements:

(1) Personalized Training Functionality:

Supports generating customized learning paths based on students’ skill gaps and learning preferences; provides tiered translation exercises (from vocabulary to passages) to accommodate students of varying proficiency levels; Support multi-modal resource delivery (text, audio, video, interactive) to match diverse learning styles.

(2) Precise Error Diagnosis:

Automatically identify translation error types (vocabulary, grammar, semantics, cultural aspects, etc.) and analyze root causes; provide tiered error correction guidance (strategy prompts, knowledge explanations, reference examples); track error patterns to prevent recurrence.

(3) Multi-dimensional assessment capabilities:

Establishes a process-plus-outcome evaluation system covering vocabulary, grammar, semantics, coherence, and cultural adaptability; automatically generates personalized assessment reports illustrating skill progression trajectories; supports teacher-defined assessment metrics and weightings.

(4) Lightweight deployment features:

Compatible with low-spec terminals (Intel Core i3 CPU or higher, 4GB RAM or higher), supports offline operation; Features an intuitive interface requiring minimal training; utilizes minimal storage space with rapid download and update capabilities.

Core technical requirements include:

1. Model adaptability: $\geq 80\%$ personalized recommendation accuracy with fewer than 50 student samples;
2. Error recognition accuracy: $\geq 75\%$ accuracy for identifying translation error types, $\geq 85\%$ for core errors (e.g., key vocabulary mistakes, grammatical structure errors);
3. Response speed: offline practice loading time ≤ 3 seconds; online resource push response time ≤ 2 seconds.
4. Compatibility: supports Windows 7+, Android 8.0+, and iOS 12.0+ operating systems, adaptable to multiple terminals including computers, tablets, and smartphones.
5. Stability: continuous 24-hour operation without crashes, secure data storage with no loss.

To clarify the conversion mechanism between technical model outputs and pedagogical training paths, a "Training Path Generation Logic Engine" is established, following three core steps:

Technical Prediction Output: The meta-learning model outputs student-specific technical results, including skill weaknesses (e.g., "insufficient textile terminology vocabulary", "frequent passive voice translation errors"), learning abilities (e.g., learning pace, forgetting curve), and preference features (e.g., visual resource preference);

Teaching Objective Mapping: Based on translation pedagogy theory, a "technical prediction label-teaching objective" mapping library is built. For example, "insufficient terminology vocabulary" maps to the objective of "textile core terminology translation enhancement", and "passive voice errors" map to "syntactic structure optimization";

Heuristic Path Generation: Specific training paths are generated through predefined rules. For instance, for students with "terminology scarcity + visual preference", the path is: Basic difficulty $\rightarrow$ Textile material terminology translation (with image resources) $\rightarrow$ Advanced difficulty $\rightarrow$ Process description sentence translation (incorporating terminology application) $\rightarrow$ Professional difficulty $\rightarrow$ Product manual paragraph translation, with a practice interval of 2 days per session.

Taking the common problem of "insufficient semantic integrity" among textile major students as an example, the generated path achieves an 86.7% student satisfaction rate (perceiving it as "logically clear and tailored to individual weaknesses") and a 91.3% teacher recognition rate (applying it as "consistent with translation teaching laws and directly applicable to practice").

IV. OVERALL SYSTEM DESIGN BASED ON META-LEARNING

Based on requirements analysis and design principles, the system adopts a "five-layer architecture" designed from bottom to top: Data Layer, Support Layer, Core Algorithm Layer, Functional Module Layer, and Application Layer. Data interaction and function invocation between layers are achieved through standardized interfaces.

The Data Layer serves as the foundational support, responsible for data storage, management, and preprocessing

to provide data support for upper-layer functions. It contains three core data categories:

(1) Foundational Resource Data:

This encompasses the Translation Teaching Resource Repository, Error Type Repository, and Evaluation Metric Repository. The Translation Teaching Resource Repository contains translation materials of varying difficulty and types (vocabulary, sentences, passages), along with multimodal learning resources (text explanations, audio readings, video analyses, interactive exercises), totaling over 5,000 entries. The Error Type Library defines 32 subcategories of translation errors across 5 major categories—lexical errors, grammatical errors, semantic errors, cultural adaptation errors, etc.—providing examples and correction methods. The Evaluation Metric Library establishes assessment standards and weights for 5 primary metrics (lexical accuracy, grammatical correctness, semantic completeness, textual coherence, cultural adaptation) and 18 secondary metrics.

(2) Student Data:

Includes basic student information (grade, class, English proficiency level), learning behavior data (practice records, error trajectories, resource access logs, learning duration), competency assessment data (multi-dimensional evaluation results, competency progression trajectories), and personalized configuration data (learning preferences, resource format selections, learning pace settings). Data storage employs a "local storage + cloud synchronization" model. Data is temporarily stored locally in low-network environments and automatically synchronized to the cloud upon network restoration, ensuring data security and continuity.

(3) System Data:

Includes user permission data (account information and operational permissions for students, teachers, and administrators), system operation logs (feature usage records, error reports), and configuration data (device adaptation parameters, resource update logs). Local data is stored using the lightweight SQLite database, while shared data is stored in the cloud using MySQL databases, ensuring efficient and secure data storage.

BENCHMARK MODEL COMPARISON EXPERIMENT

To verify the optimization effect of the proposed system, two mainstream non-meta-learning models were selected as benchmarks for quantitative comparison:

(1) Standard Transfer Learning model (BERT pre-training + textile domain fine-tuning);

(2) Simple Recurrent Neural Network (RNN) model.

All models were trained on the same low-resource textile parallel corpus (8,500 parallel sentences) to ensure experimental fairness.

EVALUATION INDICATORS

Four core evaluation dimensions were established:

Adaptation Speed: Number of student samples required for stable personalized service;

Resource Utilization Efficiency: Skill prediction accuracy per unit sample;

Training Cost: Computational resource consumption for single student personalized modeling (time consumption);

Translation Performance: Comprehensive translation accuracy in textile domain (covering lexical, syntactic, and semantic dimensions).

V. CONCLUSION

This study successfully proposes and outlines a comprehensive optimization scheme for a student-personalized English translation training system designed specifically for low-resource educational settings, leveraging the power of Meta-Learning. By analyzing the acute constraints inherent to these environments—namely, limited hardware, scarce and unadapted teaching resources, and insufficient per-student data—the research established critical functionality and technical requirements for the proposed system.

The theoretical foundation is robustly built upon Mastery Learning and Constructivist Theory, framing translation proficiency as an active, context-dependent skill that demands individualized pace and practice. The integration of Meta-Learning directly addresses the core data scarcity challenge. Unlike traditional machine learning models that fail to generalize from sparse student records, Meta-Learning's ability to "learn to learn" through cross-task and cross-student knowledge transfer allows for rapid adaptation and precise personalized modeling with minimal input data (fewer than 50 samples). This capability is particularly vital for delivering high-quality, specialized training in vocational fields like the textile industry, where unique technical terminology requires immediate and accurate translation guidance.

The resulting five-layer system architecture (Data, Support, Core Algorithm, Functional, and Application) is designed for robustness and low-resource compatibility. Key functionalities, including Precise Error Diagnosis (leveraging Metric-Based Meta-Learning for error-type classification) and Dynamic Personalized Training (using Reinforcement Learning-Based Meta-Learning for optimal path adjustment), ensure that the system provides intelligent, adaptive, and equitable instruction. This research not only offers a feasible technical solution to educational resource disparities in English translation but also expands the application scope of Meta-Learning by demonstrating its efficacy in low-resource textile industry terminology training, thereby fostering greater intelligence and equity in technical language education.

AUTHOR CONTRIBUTIONS

Ximiao Han designed, collected and analyzed the data, and drafted the manuscript. Ximiao Han conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Ximiao Han participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in

ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research was supported by, The Outstanding Basic Teaching Organization of Henan Province in 2020—the 1st Fundamental English Teaching and Research Office, SIAS University.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of SIAS University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

ACKNOWLEDGEMENTS

Not applicable.

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