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Research on Data-Driven English Personalized Teaching Design in Smart Classrooms

Linlin Li
School of Foreign Languages, Shenyang Jianzhu University
Liaoning Shenyang, 110168, China

Abstract: In the current era of educational digital transformation, there are structural problems in English teaching such as the lack of personalized guidance, insufficient utilization of data, and long evaluation and feedback times. Based on the data-driven learning theory, this paper integrates large language models and smart classroom technologies to design personalized English teaching and proposes an implementation path. According to the research findings, the promotion of smart classroom data is to reshape the teaching process into a cycle of language data occurrence - processing - analysis, and using "ad hoc data collection" to break the "data islands" caused by traditional education. A four-dimensional teaching design framework of "data diagnosis - precise teaching - dynamic evaluation - personalized push" is proposed, including three links: pre-class learning situation profiling, in-class human-computer cooperation, and post-class layered remediation. Through the data integration throughout the process, "teaching - learning - evaluation" can be achieved in consistency. It is believed that personalized teaching in smart classrooms is not about stacking technologies, but using data as an engine, transforming teaching decisions from "experience-based judgment" to "evidence-driven", and realizing large-scale individualized teaching.

Key words: Smart Classroom; Data-driven; Personalized Education; English Teaching; Human-Machine Collaboration

I. Introduction

As the education digitalization strategy is being implemented, artificial intelligence technology is profoundly influencing foreign language teaching. The smart classroom, through the integration of intelligent terminals, big data analysis and AI algorithms, has created a technical foundation that resolves the opposition between "large-class teaching" and "personalized guidance". However, currently, the application of technology in English teaching basically only stays at the superficial level of correcting grammar and automatic scoring, and there are problems such as low efficiency in data utilization, information isolation between different platforms, and lagging evaluation feedback. As a result, "data islands" have emerged during the process of quality improvement.

In this situation, how to prioritize the promotion of data, restructure the design concept and operational form of English personalized teaching, has become a practical problem that must be addressed. This research, leveraging the data processing capabilities of large language models and the accompanying collection methods of smart classrooms, has explored three core issues: How can smart classrooms collect useful teaching data? How do data influence personalized teaching decisions? How can a teaching planning framework guided by data be established? Through theoretical analysis and case verification, it aims to provide a comprehensive reference for the innovation of English teaching in the intelligent era.

II. Theoretical Foundation of Data-driven Smart Class

2.1 Data-Driven Learning Theory

Data-Driven Learning (DDL), first proposed by John, is a learning method where learners discover language patterns by observing, analyzing, and summarizing real language data. It transforms language learning from "memorizing rules" to

"finding data", providing a new epistemological foundation for technology-enriched education. In the context of educational informatization, the concept of Data-Driven Learning has also been expanded. Every moment of interaction between students and intelligent platforms, such as answering questions, leaving answer traces, modifying handwriting, voice input, and conversation logs, will become data that can be collected and analyzed, and will form a constantly changing "digital learning archive".

The key to data-driven learning lies in "companion data collection", which means that the system automatically collects the behavioral data of students throughout the entire process of pre-class preparation, in-class interaction, and post-class consolidation. Through algorithm models, a student profile can be formed, allowing teachers to identify common difficulties and individual differences. It has solved the problem of traditional teaching where "process data disappears and only the final assessment remains", transforming teaching evaluation from "evaluating results" to "tracking the process".

2.2 Technological Empowerment of Large Language Models

Large language models (LLMs) are based on the Transformer architecture and can perform scenario learning, chain-of-thought reasoning, and multi-round conversations. Unlike traditional AWE, LLMs use a generative pre-training approach to learn long-range semantic dependencies in the text, breaking down the complex language analysis process into a series of consecutive reasoning steps. This means that the machine's processing of writing data is no longer a simple lexical scan, but is handled at the logical level, converting human abstract thinking activities into data streams.

In teaching applications, LLMs can perform intelligent diagnostic of learning situations. Firstly, they offer personalized teaching applications, diagnosing learning situations and being able to intelligently identify students' vocabulary shortages, grammar deficiencies, and logical flaws in their language output. Secondly, they provide immediate interactive feedback, not by giving answers directly, but by allowing students to correct their mistakes through multiple rounds of conversation. Thirdly, they generate tiered resources based on students' different levels, adjusting the difficulty of tasks and content adaptability accordingly. All these make LLMs an important link between data collection and teaching decision-making.

III. The Current Reality of Lack of Personalized Teaching in English Education

Although educational informatization reform has been ongoing for many years, the personalized needs in English teaching have not been well met. The main reasons for this predicament are as follows:

3.1 Data Islands and Information Fragmentation

In college English teaching, the MOOC platform records study duration, the grading system calculates grammar mistakes, and the administrative system stores final grades. However, these platforms are often not produced by the same company, and their data standards are different, as are their interfaces. As a result, the highly valuable "learner data" is stored separately, and some courses are even abandoned after completion. Therefore, teachers are unable to draw a long-term language growth picture for students, and teaching decisions can only rely on partial information from a single exam, making it very difficult to track and understand the growth process.

3.2 Feedback Delay and One-sided Evaluation

In the traditional teaching model, the feedback cycle for English writing and oral practice is very long. Although the teacher has used an automatic grading system to reduce some workload, there are still limitations in diagnosing deep-level abilities such as paragraph structure, logical reasoning, and style. Students only receive a rough score, lacking the analysis of "the language issues behind the score", which prevents them from reflecting and making

revisions. The teaching evaluation has become a kind of "labeling" of the outcome rather than a "processal dialogue" that promotes learning.

3.3 Homogenization of Teaching and Disconnection from Individual Differences

The structure of large-class teaching inherently has this problem. Teachers cannot pay attention to each student's starting point and learning speed. In an English class, some students with weak foundations cannot keep up with the pace, while some students with extra learning ability are left "starving". Uniform teaching content and uniform teaching pace are difficult to meet the differentiated needs. Even if teachers want to implement individualized teaching, they cannot make correct decisions based on the learning data in their hands. They can only rely on their own experience to make guesses.

IV. Data-driven Personalized Teaching Design Framework for Smart Classrooms

In response to the aforementioned challenges, the author proposed a teaching design framework consisting of four aspects: "Data Diagnosis - Precise Instruction - Dynamic Evaluation - Personalized Push". These aspects were integrated into various stages of the entire classroom teaching process, including before, during, and after classes, thereby establishing a circular educational system driven by data.

4.1 Before Class: Data Diagnosis and Student Profile

The prerequisite for personalized teaching is precise understanding of students' learning situations. In the smart classroom environment, teachers can issue intelligent pre-class tasks or conduct pre-class learning status checks through the platform. At this time, the system will automatically collect students' responses and generate a student learning situation analysis report covering various dimensions such as accuracy rate, weak knowledge points, average response time, etc. This allows teachers to know the starting point of the teaching before the class, the common problems existing in the entire class as well as individual differences, and enables them to adjust the key points and difficulties of teaching and layered activities in a targeted manner.

According to practical cases, in English listening and speaking classes, teachers use the AI system for pre-class vocabulary quizzes and text reading assessments. The system will immediately provide feedback on the words and sentence patterns that are more frequently incorrect. At this point, the teacher can focus on explaining these difficult points in the class, achieving "learning-based teaching". Data-driven lesson planning transforms teaching plans from "experience-based estimation" to "based on evidence", improving the accuracy of teaching.

4.2 In Class: Data Navigation and Human-Machine Collaboration

As the primary venue for teaching, the classroom plays a crucial role in the data-driven instructional design process. Teachers utilize the real-time feedback from intelligent terminals to adjust their teaching pace and communication methods with students. This is mainly manifested in the following aspects:

Instant assessment of learning situation: Utilize functions such as "class-wide response", "race to answer", and "random selection" to quickly understand students' responses. Once the correct rate of the entire class reaches 85%, questions can be directly asked to those who made mistakes, eliminating the need for students to practice again. Thus, "data guidance" enables teachers' explanations to shift from "covering all aspects" to "targeted".

Intelligent Listening and Speaking Training: During the oral class, the AI system can promptly evaluate each student's pronunciation and score it based on four dimensions: accuracy, fluency, completeness, and naturalness. Words with incorrect pronunciation will be circled in red, and the teacher can refer to this when correcting the pronunciation. The virtual person conversation combined with three-

dimensional voice assessment enables students to be immersed in the communication environment, reducing the pressure of speaking and giving them the urge to "want to say".

Tiered task delivery: Based on the data from the pre-class diagnosis, different tasks are pushed to students in the class. Students with weak foundations spend most of their time practicing core vocabulary and sentence structures, while those with more advanced skills can attempt situational conversations and express their thoughts, achieving "different learning within the same class".

4.3 After-class: Data Integration and Personalized Push Notifications

The after-class phase is the iterative and consolidation stage of teaching. The smart classroom platform automatically saves all the interactive data and learning trajectories from the class and generates a classroom teaching report as well as a digital file for the students. Based on this report, the teacher reflects on the effectiveness of the class, considers whether the lesson design was good, and identifies areas that need improvement, and then formulates the teaching plan for the next class.

In terms of personalized consolidation, the system can, based on the student's learning profile, push different levels of homework to different students, and personalize the tasks. For students with poor vocabulary, it will push vocabulary assessments, and for students with difficult expression, it will push situational sentence creation. Truly achieving "one-on-one personalized" after-class consolidation. "Electronic Writing Archives" have also emerged in some schools, continuously tracking the revision process and thinking changes of students from the initial draft to the final version, transforming teaching evaluation from "one-time scoring" to "tracking growth".

V. Key Supports for the Implementation of Personalized Teaching

5.1 Teachers' Digital Literacy and Role Transformation

The data-driven personalized teaching has brought new demands for teachers. They need to understand the student assessment reports, be able to create high-quality prompts, and be able to transform data into teaching decisions. The positioning of teachers is shifting from "knowledge transmitters" to "student situation interpreters", "classroom debuggers", and "precise education designers". Schools need to provide specialized training to enhance teachers' data analysis capabilities and skills in using AI tools, guiding teachers to progress from "being able to use tools" to "being skilled at using technology".

5.2 Reconfiguration of the Teaching Evaluation System

For personalized teaching, the evaluation method should shift from "summative assessment" to "process-based diagnosis". It is suggested to adopt a multi-dimensional and diverse evaluation approach such as "AI language assessment + teacher's thinking assessment + student's experience assessment". AI will immediately provide opinions on the correctness and fluency of the language, while the teacher focuses on evaluating high-order thinking and cross-cultural literacy. Students conduct self-assessment and mutual assessment to enhance their reflective awareness. The evaluation indicators should cover process data such as classroom participation level, modification and iteration times, and the depth of interaction with AI, reducing the weight of summative examinations and encouraging students to value improvement in abilities rather than the acquisition of scores.

5.3 Balancing Technical Ethics and Subjectivity

In the process of using data to drive teaching, we must avoid falling into the trap of over-reliance on technology and neglecting the students' autonomy. Some scholars argue that if students merely use large language models to simply replicate the essays they have written before without thinking about making

any changes, it will limit their ability for autonomous learning. Therefore, in the teaching design, we must adhere to the principle of "human-machine collaboration". AI provides data support and immediate feedback, but the guidance of advanced thinking, emotional stimulation, and value orientation still need to be carried out by teachers. We must also pay attention to data security and privacy protection to ensure that the use of technology complies with ethical standards.

VI. Conclusion

This study, from the perspective of data-driven approach, has contemplated and analyzed the personalized teaching design for English in smart classrooms. The main conclusion is that personalized teaching driven by data is not merely a simple "overlay" of technologies; instead, it uses data as the engine and focuses on the word "learning", achieving a processual transformation of teaching decisions from experience to evidence and from uniformity to stratification. The three loops of pre-class learning situation profiling, in-class human-computer collaboration, and post-class targeted remediation form a closed loop, providing an operational solution for large-scale individualized teaching.

Future research can further validate the teaching effectiveness of this framework on a larger scale, and explore the matching methods under different educational stages and different types of lessons. It is also necessary to continue to ponder the dialectical relationship between technology assistance and the student's autonomy. The ultimate goal of technology is still to promote the development of every learner, enabling them to follow the path that suits them best. This is the true essence of educational equity and the meaning of intelligent education.

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