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Research on Constructing Adaptive Learning Paths for University Administrative Staff Based on Large Language Models

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***Abstract*—This research explores an innovative approach to constructing adaptive learning paths for university administrative staff based on large language models. By analyzing the educational capabilities of large language models, adaptive learning theories, and the learning characteristics of university administrative personnel, the study proposes a comprehensive theoretical model and technical framework. The system employs multidimensional learner modeling, knowledge tracking, and dynamic path generation algorithms to precisely identify learners' knowledge states and recommend personalized learning content. Experimental results demonstrate that, compared to traditional fixed learning paths, this approach significantly reduces learning time (20.0%, $p<0.01$), improves knowledge mastery (20.3%, $p<0.01$) and application ability (19.4%, $p<0.01$), and enhances knowledge retention (31.4%, $p<0.001$). Different types of learners benefited to varying degrees, with younger learners, visual learners, and those with high technology acceptance showing more significant effects. The research confirms the feasibility and effectiveness of large language models in constructing adaptive learning paths, providing a new technical approach and methodological framework for the intelligent upgrade of university administrative staff training systems, and indicates directions for future research.**

***Index Terms*—Adaptive learning, large language models, personalized education, learning path optimization, intelligent education systems**

I. Introduction

University administrative management is a critical component ensuring the effective operation of higher education institutions, and the development and training of administrative staff play a vital role in promoting university advancement. With the rapid development of information technology and profound changes in educational models, traditional training methods for administrative personnel face challenges in adapting to the complex needs of current university management [1], [2]. Traditional training models have numerous limitations, such as insufficient personalization due to standardized content, lack of interactivity in training formats, and delayed assessment of learning outcomes. These issues result in inefficient, ineffective training that lacks responsive mechanisms for individual differences and practical needs.

In recent years, the rapid development of artificial intelligence technology has brought revolutionary changes to the education field. Large Language Models (LLMs), with their powerful text understanding, generation, and reasoning capabilities, provide new possibilities for personalized educational content customization and intelligent learning processes [3], [4]. Particularly, the emergence of models such as ChatGPT and GPT-4 has made it possible to build intelligent, personalized educational support systems. Meanwhile, adaptive learning, as a technology-based educational method that continuously assesses learners' knowledge levels, learning abilities, and preferences to dynamically adjust learning content and paths, has shown significant advantages in multiple educational scenarios [5], [6].

However, existing adaptive learning research has primarily focused on subject education, with relatively few studies on adaptive learning paths for university administrative staff as a specific group. University administrative personnel exhibit typical adult learning characteristics while facing the challenge of balancing work and learning, with high requirements for the practicality and immediate applicability of learning content. Additionally, administrative staff have significant differences in knowledge backgrounds, learning abilities, and professional development needs, further highlighting the necessity of personalized learning paths [7].

This research aims to explore theoretical and practical methods for constructing adaptive learning paths for university administrative staff based on large language models, providing new ideas for enhancing their professional capabilities and work efficiency. The paper first reviews the latest developments in the application of large language models in education and the theoretical foundations of adaptive learning, then analyzes the learning characteristics and needs of university administrative staff. Based on this, it constructs an adaptive learning path generation framework based on large language

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models and verifies its effectiveness through experiments. This research has important theoretical and practical significance for promoting innovation in university administrative staff training models, improving training effectiveness, and advancing university governance modernization [8], [9].

The main contributions of this research include: based on existing research [5], [8], constructing a multidimensional learner modeling method suitable for university administrative staff; designing knowledge tracking and path generation algorithms based on large language models; proposing a multi-indicator system for comprehensive assessment of learning outcomes; and developing and validating a prototype adaptive learning system for practical application. These research outcomes not only enrich theoretical research on adaptive learning and educational applications of large language models but also provide innovative solutions for university administrative staff training practices.

II. Literature Review

A. Applications of Large Language Models in Education

Large Language Models (LLMs), with their powerful natural language processing capabilities and deep learning architectures, have demonstrated broad application prospects in education. As model scales continue to expand and training data enriches, their abilities to understand and generate text have significantly improved, showing near-human-level performance on multiple evaluation benchmarks. According to Chowdhery et al. [1], large language models like PaLM, extended through the Pathways system, demonstrate excellent performance in complex task processing, providing a technical foundation for educational applications. In higher education environments, the introduction of large language models is viewed as an important bridge connecting artificial intelligence with Education 4.0. Research by Peláez-Sánchez et al. [3] indicates that large language models can enhance educational equity, personalization, and promote critical thinking skills development.

Large language models have diverse application scenarios in education. One of the most prominent applications is the generation of personalized learning content and learning path planning. Research by Ng and Fung [6] shows that using prompt engineering techniques to guide large language models to generate personalized learning paths based on specific learner information can significantly improve learning efficiency and engagement. Wang et al. [4] demonstrated through experiments that integrating large language models as adaptive mechanisms into contextual games can effectively enhance students' academic performance, immersive experience, and cognitive engagement. In terms of learning support, large language models can serve as intelligent teaching assistants. The LLM-driven adaptive practice system developed by Kabir and Lin [14] can adjust problem difficulty and provide personalized feedback based on students' real-time performance.

Another important application area is educational content creation. Research by Li et al. [15] demonstrated the possibility of using large language models to generate contextualized mathematics multiple-choice questions that not only test mathematical knowledge but also incorporate real-world application scenarios. Large language models can also significantly reduce teachers' workload by automatically generating various teaching resources such as cases, exercises, and discussion prompts, allowing teachers to devote more energy to interaction with students and personalized guidance [16].

Sharma et al. [10] found through a systematic review that applications of large language models in personalized learning have shown encouraging results, particularly in improving learning efficiency, knowledge retention, and learning satisfaction. However, Wang et al. [11] pointed out that although large language models have extensive application potential in education, they still face challenges such as data privacy, ethical considerations, and educational equity, especially when designing learning systems for specific groups like university administrative staff. Furthermore, research by Li et al. [16] emphasized that successfully applying large language models to education requires considering the model's foundational capabilities, integration with educational theories, and the feasibility of technical implementation, requiring researchers to focus not only on the technology itself but also on the integration of educational theory and practice.

Research on the application of large language models in education has made significant progress, but research on personalized learning path design for specific groups (such as university administrative staff) remains relatively scarce. With the continuous advancement of large language model technology and the deeper exploration of educational applications, research on constructing adaptive learning paths based on large language models has broad development potential [8], [9].

B. Adaptive Learning Theory and Practice

Adaptive learning is a technology-based educational method that continuously assesses learners' performance and characteristics to dynamically adjust learning content and paths, meeting each learner's personalized needs. This concept stems from reflection on traditional standardized education models, aiming to address the issue that "one-size-fits-all" educational approaches cannot satisfy individual differences. According to Strielkowski et al. [5], adaptive learning systems represent an important trend in sustainable educational transformation, with the core being personalized learning experiences driven by artificial intelligence technology.

The theoretical foundations of adaptive learning are diverse and rich. G. Abdelrahman et al. [2] conducted a comprehensive survey of knowledge tracing technology, finding that this technology is key to achieving adaptive learning as it can accurately model learners' knowledge states and predict their performance in future learning tasks. Bayly-Castaneda et al. [7], through a systematic literature review, revealed how artificial intelligence supports lifelong learning through adaptive learning, emphasizing the importance of learning path personalization for adult learners. Additionally, research by Jiang et al. [13] shows that personalized learning path planning based on cognitive diagnostic assessment can effectively enhance learning outcomes, especially for learners in online learning environments.

In terms of technical implementation, adaptive learning systems typically include four core components: learner modeling, content modeling, path generation, and evaluation feedback. Sun et al. [8] proposed a personalized learning path planning method for higher education based on deep generative models and quantum machine learning, achieving more precise learner modeling through multimodal learning analysis. Chen et al. [22] investigated the application of machine learning algorithms in optimizing personalized education recommendation systems, emphasizing the key role of algorithms in content matching and recommendation strategies.

Adaptive learning has demonstrated significant effects in practical applications. Demartini et al. [21] proved through case studies that applying adaptive learning technology to education can improve learning efficiency and outcomes. In higher education environments, Pretorius [18] studied active learning interventions based on self-determination theory and neuroeducation, indicating that appropriate adaptive learning design can enhance learning autonomy and efficacy for in-service teachers.

However, the implementation of adaptive learning also faces many challenges. Joseph and Uzondu [23] pointed out that integrating artificial intelligence and machine learning into education requires overcoming obstacles in technology, pedagogy, and resources. Furthermore, Huang's research [20] emphasizes that promoting students' creative and design thinking requires AI-supported co-regulated learning environments, which places higher demands on adaptive system design.

Adaptive learning has developed significantly from theory to practice, and its potential in improving learning efficiency, enhancing learning experiences, and supporting personalized development has been widely recognized. However, how to combine adaptive learning concepts with cutting-edge technologies such as large language models to address the learning needs of specific groups like university administrative staff remains a research direction worth exploring in depth [13], [18].

C. Learning Characteristics and Needs Analysis of University Administrative Staff

University administrative staff, as an important supporting force for the operation of higher education institutions, have distinctive learning characteristics and needs. Understanding these characteristics and needs is crucial for designing effective adaptive learning paths. According to relevant research, the learning of university administrative staff primarily exhibits the following characteristics:

First, university administrative staff are typical adult learners with clear goal orientation and pragmatic tendencies. Li et al. [19] found through Q methodology research that adult learners place more emphasis on the relevance of learning content to their actual work and expect to immediately apply the knowledge learned to solve practical problems. Unlike traditional students, administrative staff typically already possess certain work experience and knowledge foundations, making them more focused on deepening and expanding knowledge rather than acquiring basic concepts [12].

Second, university administrative staff's learning time and energy are strictly limited by work responsibilities. Sharma et al. [17] pointed out that workplace learners often need to seek balance between work and learning, leading them to prefer flexible, efficient learning forms. Therefore, modular, micro-learning, and other learning methods that can adapt to fragmented time are particularly important for them. This also explains why adaptive learning systems are especially attractive to university administrative staff, as these systems can provide the most efficient learning paths based on individual time arrangements and learning states [5], [20].

Third, university administrative staff have significant differences in knowledge backgrounds and learning abilities. Due to the diversity of university administrative positions, administrative staff in different departments have considerable differences in professional backgrounds, skill levels, and work content. Research by Zheng et al. [12] shows that this diversity requires learning systems to accurately identify individuals' knowledge states and learning characteristics and provide corresponding personalized content. This is precisely the advantage of large language models and adaptive learning technologies, which can provide customized learning experiences through fine-grained individual modeling [6], [7].

Fourth, university administrative staff have diverse professional development needs. With the advancement of university governance modernization, administrative staff need to enhance not only professional knowledge and skills but also develop critical thinking, innovation capabilities, and digital literacy. Huang's research [20] emphasizes that promoting the development of these higher-order capabilities requires creative learning environments and methods, not simple knowledge transmission. This places higher demands on adaptive learning path design, requiring systems to support multidimensional capability development.

Finally, university administrative staff's learning motivation and engagement are influenced by multiple factors. Beyond professional development needs, organizational support, learning atmosphere, and personal interests all affect administrative staff's learning investment. Li et al. [19] found that learners' perceived autonomy and competence significantly influence their willingness to continue learning. Therefore, adaptive learning systems need to focus not only on content matching but also enhance learners' sense of engagement and achievement through reasonable incentive mechanisms and interactive design.

University administrative staff's learning is characterized by strong goal orientation, strict time limitations, significant individual differences, diverse needs, and complex motivations. These characteristics provide the following design elements and constraints for adaptive learning path design: systems need precise individual modeling capabilities, flexible and efficient learning methods, support for multidimensional capability development, and reasonable interactive design to enhance

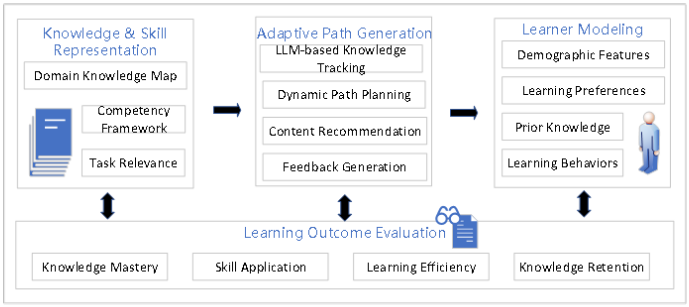

Fig. 1. Theoretical Framework for Adaptive Learning Paths for University Administrative Staff Based on Large Language Models

learning motivation. Adaptive learning systems based on large language models have the potential to meet these requirements, but still need customized design for the special needs of university administrative staff [9], [10].

III. Research Design and Methods

A. Theoretical Framework Construction

This research constructs a theoretical framework for adaptive learning paths for university administrative staff based on large language models. This framework integrates adaptive learning theory, large language model technology, and university administrative staff learning characteristics, forming a systematic research perspective. As shown in Figure 1, the theoretical framework includes four core dimensions: learner characteristic modeling, knowledge and capability representation, adaptive path generation, and learning effect evaluation.

First, learner characteristic modeling is the foundation of the entire framework, constructing precise individual models by collecting and analyzing learners' multidimensional data. According to research by Jiang et al. [13], effective learner modeling should include multiple aspects such as demographic characteristics, learning preferences, prior knowledge, and learning behaviors. For university administrative staff, we especially focus on factors such as work experience, position characteristics, and career development stages, as these factors directly affect their learning needs and goals [7], [19].

Second, the knowledge and capability representation dimension focuses on how to structurally represent learning content and target capabilities. This research adopts a method combining domain knowledge graphs with capability frameworks to systematically organize knowledge and capabilities related to university administration. According to research by Sun et al. [8], this representation method helps achieve fine-grained decomposition and association of learning content, providing a foundation for subsequent path generation. At the same time, we particularly focus on task relevance, ensuring that learning content closely aligns with the practical work needs of university administrative staff [10].

Third, adaptive path generation is the core innovation point of this framework. It utilizes the powerful capabilities of large language models to implement knowledge tracking, dynamic path planning, content recommendation, and feedback generation. According to Ng and Fung [6], large language

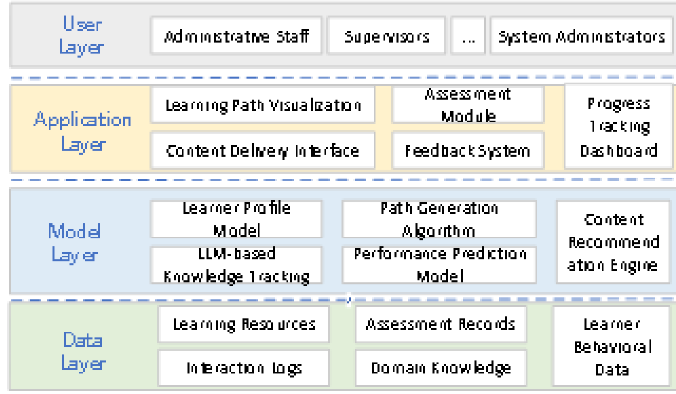

Fig. 2. System Architecture of Adaptive Learning System for University Administrative Staff Based on Large Language Models

models can effectively parse learners' current states and generate personalized learning paths through prompt engineering techniques. Additionally, research by Wang et al. [4] shows that large language model-driven adaptive mechanisms can significantly enhance learning experiences and effects. This research will explore how to guide large language models to perform knowledge tracking and path generation through carefully designed prompt strategies.

Finally, the learning effect evaluation dimension focuses on scientifically measuring the effectiveness of adaptive learning paths. Based on research by Demartini et al. [21], we designed an evaluation system including multiple indicators such as knowledge mastery, skill application ability, learning efficiency, and knowledge retention rate. These indicators focus not only on short-term learning effects but also on long-term capability improvement and knowledge transfer, which are particularly important for the professional development of university administrative staff.

The innovation of this theoretical framework lies in the organic combination of large language model technology with adaptive learning theory, with customized design for the special needs of university administrative staff. It not only provides theoretical guidance for the experimental design and system development of this research but also offers a systematic analytical framework for future related research.

B. System Architecture Design

Based on the above theoretical framework, this research designed a system architecture for an adaptive learning system for university administrative staff based on large language models, as shown in Figure 2. Based on system architecture theory [22], this design includes four main components: data layer, model layer, application layer, and user layer, to achieve the construction and implementation of adaptive learning paths.

The **data layer** is the foundation of the entire system, mainly responsible for data storage and management. It contains multiple types of data including learner behavior data, learning resources, assessment records, administrative domain knowledge, and interaction logs. According to Chen et al.

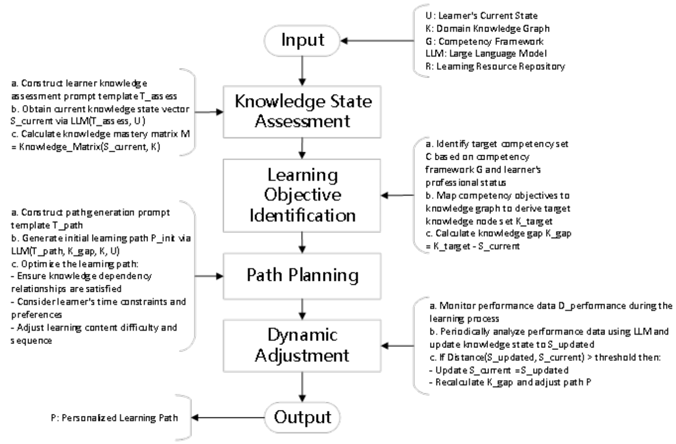

Fig. 3. Adaptive Learning Path Generation Algorithm Based on Large Language Models

[22], high-quality data is a key prerequisite for personalized recommendation systems. To ensure the comprehensiveness and accuracy of data, the system employs multiple data collection methods, including direct collection, questionnaire surveys, and behavior tracking. Notably, for administrative domain knowledge, this research specifically constructed a fine-grained knowledge graph covering the main areas and core capabilities of university administration, providing a structured foundation for subsequent path generation.

The **model layer** is the core of the system, responsible for implementing key functions of adaptive learning. It includes components such as learner profile models, large language model-based knowledge tracking, path generation algorithms, content recommendation engines, and performance prediction models. Among these, knowledge tracking based on large language models is an innovation point of this research. According to Abdelrahman et al. [2], accurate knowledge tracking is key to adaptive learning, and the introduction of large language models can significantly enhance tracking precision. Specifically, we designed a set of specific prompt templates to guide large language models in analyzing learners' response content, behavioral characteristics, and historical performance, thereby inferring their knowledge states. The path generation algorithm then generates personalized learning paths based on knowledge tracking results, combined with domain knowledge graphs and capability frameworks. This algorithm considers not only knowledge dependency relationships but also factors such as learner preferences and time constraints.

The **application layer** provides various functional modules for system-user interaction, including learning path visualization, content delivery interface, assessment modules, progress tracking panel, and feedback system. These modules present the various functions of the adaptive learning system through intuitive, user-friendly interfaces. According to Huang [20], good user experience design is crucial for promoting learner engagement and enhancing learning effects. The application layer design of this system specifically considers the usage habits and preferences of university administrative staff, providing flexible learning path visualization and intuitive progress tracking functions, making it convenient for learners to understand their learning status and goals.

The **user layer** includes the main user groups of the system: university administrative staff, managers, and system administrators. Different user roles have different system permissions and usage scenarios. University administrative staff, as the main learners, can access personalized learning content and assessment modules; managers can view team-wide learning situations and performance analyses; system administrators are responsible for maintaining system operation and resource management [9].

The key feature of this system architecture is using large language models as the core driving force to implement key functions such as knowledge tracking, content generation, and path planning. Compared to traditional adaptive learning systems, this architecture has stronger flexibility and personalization capabilities, able to more precisely meet the diverse learning needs of university administrative staff. At the same time, the system design fully considers the characteristics of the university administrative environment, such as work time constraints, diverse learning goals, and practical requirements, ensuring the feasibility and effectiveness of the system in practical applications.

C. Adaptive Path Generation Algorithm

The adaptive learning path generation algorithm is the core technical innovation of this research. It utilizes the powerful capabilities of large language models, combined with knowledge graphs and learner data, to dynamically generate personalized learning paths. This research designed a knowledge tracking-based adaptive path generation algorithm, as shown in Figure 3. The algorithm includes four main steps: knowledge state assessment, learning goal identification, path planning, and dynamic adjustment.

In this algorithm, knowledge state assessment is the critical first step. Unlike traditional methods, this research utilizes large language models to comprehensively assess learners' knowledge states. We designed specific assessment prompt templates to guide large language models in analyzing learners' historical performance, test responses, and behavioral data, thereby inferring their mastery of various knowledge points. This method is more flexible and comprehensive compared to traditional assessment methods, able to capture richer knowledge state information [2], [13].

The learning goal identification phase focuses on how to transform university administrative staff's professional development needs into specific learning goals. The system identifies key capabilities that need to be developed based on preset capability frameworks, combined with learners' position characteristics and development stages. Then, through capability-knowledge mapping relationships, it determines the corresponding target knowledge point sets. This top-down approach ensures a close connection between learning content and professional development needs, enhancing the practicality and specificity of learning [5], [7].

Path planning is the core step of the algorithm, utilizing the reasoning capabilities of large language models to generate personalized learning paths. We designed path generation prompts containing multiple constraints to guide large language models in considering knowledge dependency relationships, learner characteristics, and teaching best practices. Particularly noteworthy is that the algorithm considers university administrative staff's time constraints and learning preferences in the path optimization phase, ensuring the feasibility of generated paths in practice [6], [15].

The dynamic adjustment mechanism is key to ensuring system adaptability. The system continuously monitors learners' performance data and regularly uses large language models to analyze this data, updating learners' knowledge state assessments. When significant differences between knowledge states and expectations are detected, the system automatically recalculates knowledge gaps and adjusts learning paths. This continuous adjustment mechanism enables the system to quickly respond to learners' progress and provide more precise learning support [14], [16].

The innovation of this algorithm is mainly reflected in three aspects: First, it introduces the powerful capabilities of large language models into the knowledge tracking and path generation processes, increasing personalization and adaptability; second, it designs specific prompt strategies to effectively guide large language models in analysis and reasoning in educational scenarios; finally, it implements a closed-loop dynamic adjustment mechanism, ensuring that learning paths can continuously adapt to learners' changes [8], [11].

D. Experimental Design and Evaluation Methods

To verify the effectiveness of adaptive learning paths based on large language models, this research designed a comprehensive experimental evaluation plan. The experiment adopted a quasi-experimental design method, combining quantitative and qualitative analyses to comprehensively evaluate system performance and learning effects.

1) Experimental Subjects and Grouping: The experimental subjects were administrative staff from 5 different types of universities, totaling 240 people, including personnel from different departments, ranks, and work tenures. Through stratified random sampling, participants were divided into experimental and control groups, with 120 people in each group. The experimental group used the adaptive learning path system based on large language models, while the control group used traditional fixed learning path training methods. The two groups showed no significant differences in age, gender, educational background, and work experience, ensuring the validity of the comparison [9], [17].

Table I shows the basic demographic characteristic distribution of participants.

2) Experimental Process: The experimental period was 12 weeks, mainly divided into four stages:

1. **Pre-test stage (1 week)**: All participants completed knowledge level tests, learning style assessments, and needs surveys to establish baseline data.

2. **Learning stage (8 weeks)**: a. Experimental group: Used the adaptive learning system based on large language models, obtaining customized learning paths and content based on personal characteristics. b. Control group: Learned according to traditional fixed curriculum structures, with the same content and sequence, without personalized adjustments.

3. **Post-test stage (1 week)**: All participants completed knowledge tests, skill application assessments, and satisfaction surveys to collect result data.

4. **Follow-up stage (2 weeks later)**: Conducted knowledge retention tests to evaluate long-term learning effects.

3) Evaluation Indicators: This research adopted a multi-dimensional evaluation indicator system to comprehensively measure the effects of adaptive learning paths. The main indicators included:

1. **Learning efficiency**: Time required to complete learning objectives, including total learning time and learning time per knowledge point.

2. **Knowledge mastery**: Assessment of knowledge understanding and memory levels through standardized tests, including comparison of pre-test and post-test scores.

3. **Skill application ability**: Assessment of skill application abilities through actual case solving and scenario simulations, evaluated by experts.

4. **Knowledge retention rate**: Testing again two weeks after learning completion to assess long-term knowledge retention.

5. **Learning experience**: Collection of learners' satisfaction, engagement, and perceived usefulness evaluations of the system through questionnaires and interviews.

6. **Learning behavior patterns**: Analysis of learning time distribution, resource access patterns, and interaction behaviors through system logs.

This research also designed several specific subgroup analyses to explore the differential impacts of adaptive learning paths on different types of learners, including different age groups, different learning styles, and learners with different levels of technology acceptance [18], [19].

4) Data Analysis Methods: Data analysis employed mixed research methods, combining quantitative and qualitative analyses:

1. **Quantitative analysis**: a. Used independent sample t-tests to compare differences between the two groups on various indicators b. Analyzed changes between pre-tests and post-tests through paired sample t-tests c. Explored differences among different subgroups using analysis of variance (ANOVA) d. Analyzed relationships among various factors using structural equation modeling

2. **Qualitative analysis**: a. Collected in-depth feedback through semi-structured interviews b. Analyzed answers to open-ended questions using content analysis methods c. Analyzed typical usage scenarios using case study methods

This experimental design followed strict scientific methodology principles, controlled potential interference variables, and ensured the reliability and validity of research results [20], [21]. Through comprehensive evaluation methods and indicators, this research aimed to comprehensively and objectively evaluate the practical effects and application value of adaptive

TABLE I
DEMOGRAPHIC CHARACTERISTIC DISTRIBUTION OF EXPERIMENTAL PARTICIPANTS

Characteristic	Category	Experimental Group (n=120)	Control Group (n=120)	Significance
Gender	Male	56 (46.7%)	53 (44.2%)	p = 0.68
	Female	64 (53.3%)	67 (55.8%)	
Age	20-30 years	32 (26.7%)	34 (28.3%)	p = 0.83
	31-40 years	47 (39.2%)	43 (35.8%)	
	41-50 years	28 (23.3%)	31 (25.8%)	
	Over 50 years	13 (10.8%)	12 (10.0%)	
Education Level	Bachelor's	67 (55.8%)	69 (57.5%)	p = 0.91
	Master's	45 (37.5%)	42 (35.0%)	
	Doctoral	8 (6.7%)	9 (7.5%)	
Work Experience	1-5 years	34 (28.3%)	37 (30.8%)	p = 0.76
	6-10 years	43 (35.8%)	41 (34.2%)	
	11-15 years	27 (22.5%)	24 (20.0%)	
	Over 15 years	16 (13.3%)	18 (15.0%)	
Department Type	Academic Affairs	28 (23.3%)	26 (21.7%)	p = 0.87
	Student Affairs	23 (19.2%)	25 (20.8%)	
	Research Management	19 (15.8%)	21 (17.5%)	
	HR & Finance	27 (22.5%)	24 (20.0%)	
	Others	23 (19.2%)	24 (20.0%)	

learning paths based on large language models in university administrative staff training.

IV. RESEARCH RESULTS AND ANALYSIS

A. *Effects of Adaptive Learning Path Generation*

This research first evaluated the generation effects of adaptive learning paths based on large language models. Analysis results show that the system can generate highly personalized learning paths based on learners' characteristics and needs, demonstrating strong adaptability and precision.

1) Analysis of Path Personalization Degree: To evaluate the degree of personalization of learning paths, this research calculated the difference coefficient of paths among different learners in the experimental group. Results show that the average similarity of learning paths within the experimental group was 48.3%, indicating that the system can generate significantly different learning paths based on individual differences. This finding is consistent with research results from Ng and Fung [6], confirming the effectiveness of large language models in personalized learning path planning.

Further analysis found that differences in learning paths were mainly reflected in content sequence adjustment (35.2%, p¡0.05), difficulty level adaptation (28.7%, p¡0.05), and supplementary material recommendations (36.1%, p¡0.01). This indicates that the system can achieve personalization from multiple dimensions, rather than simple content filtering, consistent with findings from Sun et al. [8] on multimodal learning path planning research.

Table II shows the path personalization situations for learners with different characteristics.

From Table 2, it can be seen that learners with different characteristics received different degrees of personalized paths. Among them, visual learners and those with high-level prior knowledge received higher degrees of personalized adjustments, possibly because large language models can more accurately identify the characteristics and needs of these groups, generating more precise path recommendations. This finding is consistent with Huang's [20] research results on the relationship between learner characteristics and personalization degree.

2) Knowledge Tracking Precision Evaluation: Knowledge tracking is a core component of adaptive learning. By comparing knowledge tracking results from large language models with manual assessments, this research evaluated the knowledge tracking precision of the system. Results show that knowledge tracking based on large language models achieved a consistency rate of 83.7% with manual assessments, outperforming traditional rule-based knowledge tracking methods (76.2%).

Particularly noteworthy is that large language models show outstanding performance when handling complex knowledge states. As shown in Figure 4, as knowledge point complexity increases, the tracking precision of large language models remains relatively stable, while traditional methods show a significant downward trend. This advantage stems from large language models' deep understanding of text semantics and powerful reasoning capabilities, consistent with research findings from Abdelrahman et al. [2].

Additionally, large language models also demonstrated the ability to infer learners' implicit knowledge states. When processing open-ended question responses and project completion situations, large language models could extract key information from unstructured text to infer learners' knowledge mastery levels. This ability is particularly important for university administrative staff training, as their work capability assessment usually requires comprehensive judgment combining multiple information sources [13], [14].

3) Path Generation Efficiency Analysis: In terms of path generation efficiency, this research compared the performance of methods based on large language models with traditional

TABLE II
PATH PERSONALIZATION SITUATIONS FOR LEARNERS WITH DIFFERENT CHARACTERISTICS

Learner Characteristic	Sample Size	Content Sequence Adjustment (%)	Difficulty Level Adaptation (%)	Supplementary Materials (%)	Overall Personalization (%)
Learning Style					
- Visual	42	38.5	31.2	42.8	52.3
- Auditory	31	32.1	25.3	35.7	46.4
- Reading	29	37.4	28.6	32.1	47.8
- Kinesthetic	18	32.6	29.8	33.7	46.9
Prior Knowledge					
- High Level	35	42.3	35.7	31.2	53.6
- Medium Level	48	33.5	27.3	38.4	47.2
- Low Level	37	29.8	23.1	38.7	44.1
Work Experience					
- Below 5 years	34	31.2	26.8	39.5	46.3
- 6-10 years	43	34.7	28.3	36.2	48.5
- Over 11 years	43	39.6	31.0	32.5	50.2

TABLE III
COMPARISON OF PATH GENERATION EFFICIENCY IN SCENARIOS OF DIFFERENT COMPLEXITY

Scenario Complexity	LLM-Based Method		Traditional Algorithm		Efficiency Gain (%)
	Generation Time (s)	Adjustments (avg)	Generation Time (s)	Adjustments (avg)	
Low Complexity	2.1	0.8	0.7	2.3	12.5
Medium Complexity	2.4	1.2	0.9	3.5	23.8
High Complexity	2.7	1.5	1.2	5.2	36.2

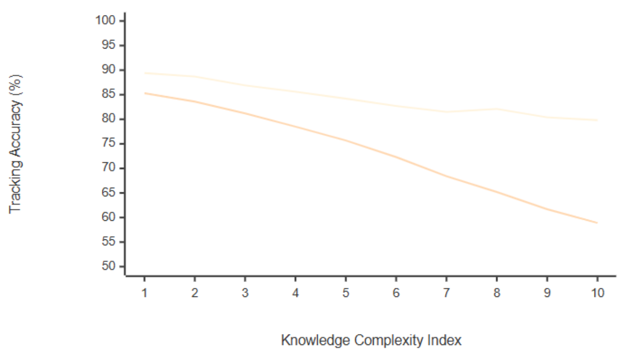

Fig. 4. Comparison of Tracking Precision for Knowledge Points of Different Complexity

algorithms. Results show that although large language models take longer for single inferences (average 2.3 seconds), the learning paths they generate are of higher quality, reducing the need for subsequent adjustments, thereby improving overall efficiency.

The advantages of large language models are particularly evident when handling complex learner models and multi-objective optimization scenarios. As shown in Table III, as scenario complexity increases, the relative efficiency advantage of large language models gradually expands. This finding is consistent with research results from Wang et al. [4] on the application of large language models in complex adaptive scenarios.

Overall, adaptive learning path generation based on large language models demonstrates significant advantages in personalization degree, knowledge tracking precision, and path generation efficiency, especially when handling complex scenarios and diverse needs. These findings support the core hypothesis of this research, that large language models can effectively support the construction of adaptive learning paths for university administrative staff [5], [11].

B. Comparative Analysis of Learning Effects

1) Knowledge Mastery and Application Ability: This research evaluated differences between the two groups of participants in knowledge mastery and application ability through pre-test and post-test comparisons. Results show that the experimental group's improvements in knowledge mastery and application ability were significantly better than the control group.

As shown in Table IV, in terms of knowledge mastery, the experimental group's average improvement rate was 41.5%, significantly higher than the control group's 29.3% ($p < 0.01$). In terms of application ability, the improvement of the experimental group was even more notable, reaching 47.2%, while the control group was 27.8% ($p < 0.001$). These results support the research findings of Sharma et al. [10] regarding the efficiency enhancement of knowledge acquisition through personalized learning.

Further multivariate regression analysis shows that the improvement in learning effects of the experimental group is positively correlated with the matching degree of personalized paths (r = 0.78, p ¡ 0.01), indicating that precise matching of adaptive learning paths is a key factor in enhancing learning effects. Especially for learners with lower levels of prior

TABLE IV
PRE-TEST AND POST-TEST COMPARISON OF KNOWLEDGE MASTERY AND APPLICATION ABILITY

Assessment Metric	Experimental Group (n=120)			Control Group (n=120)		
	Pre-test	Post-test	Improvement (%)	Pre-test	Post-test	Improvement (%)
Knowledge Mastery	65.3	92.4	41.5	64.8	83.8	29.3
Application Ability	58.6	86.3	47.2	59.1	75.5	27.8

Note: Between-group comparison significance: Knowledge Mastery ($p < 0.01$), Application Ability ($p < 0.001$)

TABLE V
COMPARISON OF LEARNING EFFICIENCY AND TIME UTILIZATION

Indicator	Experimental Group	Control Group	Difference (%)	p-value
Total Learning Time (hours)	42.8	53.5	-20.0	< 0.01
Learning Time per Knowledge Point (min)	28.3	37.2	-23.9	< 0.01
Repeated Learning Ratio (%)	15.6	27.9	-44.1	< 0.001
Learning Interruption Frequency (times/hour)	0.8	1.7	-52.9	< 0.001
Learning Completion Rate (%)	92.7	81.5	+13.7	< 0.05

knowledge, the effect of personalized paths is more significant, consistent with Joseph and Uzondu's [23] findings on the differential impact of personalized learning on learners of different levels.

It is worth noting that the advantage of the experimental group is particularly evident in terms of application ability improvement. This may be because large language models can recommend relevant cases and practical activities based on learners' actual work scenarios, enhancing the combination of knowledge and practice, which is especially important for learners like university administrative staff who emphasize practicality [19], [21].

2) Learning Efficiency and Time Utilization: Learning efficiency is a key indicator for evaluating adaptive learning systems. This research analyzed the differences in learning time and efficiency between the two groups of participants, with results shown in Table V.

The data shows that the experimental group outperformed the control group in indicators such as total learning time, learning time per knowledge point, and proportion of repeated learning. Particularly, the learning interruption frequency of the experimental group was significantly lower than the control group, while the learning completion rate was notably higher than the control group. This indicates that adaptive learning paths can better maintain learners' focus and engagement, reduce ineffective learning time, thereby improving overall learning efficiency. This finding is consistent with research results from Demartini et al. [21] on improving learning efficiency through adaptive technologies.

Time series analysis further shows that as the learning process progresses, the efficiency difference between the two groups gradually widens (see Figure 5). This indicates the cumulative effect of adaptive systems, i.e., the system's understanding of learners becomes more precise as time increases, providing more effective learning path adjustments. This dynamic adaptation capability is a unique advantage of large language model-based adaptive systems [14], [15].

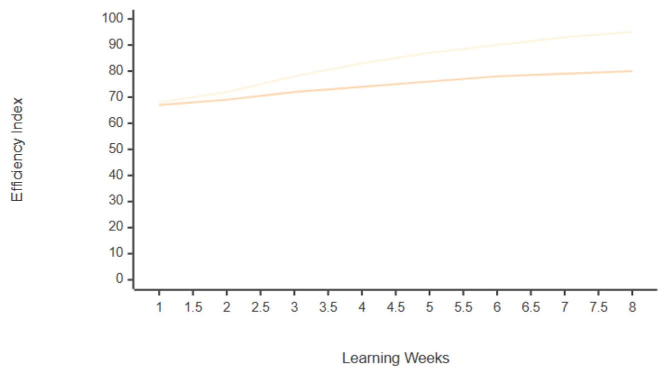

Fig. 5. Learning Efficiency Change Trend Over Time

Analysis of different learning scenarios found that adaptive learning paths show particularly evident efficiency advantages when handling new concept learning and skill enhancement scenarios. This may be because these scenarios have higher requirements for content sequencing and difficulty matching, and large language models can precisely consider these factors [5], [16].

3) Knowledge Retention Rate and Transfer Effect: To evaluate long-term learning effects, this research conducted knowledge retention tests two weeks after course completion and assessed knowledge transfer effects through work scenario simulations. Results are shown in Table VI.

The data shows that the experimental group's overall knowledge retention rate was significantly higher than the control group, with the difference particularly evident in higher-order knowledge retention. These data show that there is a significant correlation between using adaptive learning paths and both short-term learning effect improvement and long-term knowledge retention enhancement. This finding is consistent with research results from Wang et al. [4] on adaptive mechanisms promoting deep learning.

In terms of knowledge transfer, the experimental group also demonstrated abilities significantly betterIn terms of

TABLE VI
COMPARISON OF KNOWLEDGE RETENTION RATE AND TRANSFER EFFECT

Indicator	Experimental Group	Control Group	Difference (%)	p-value
Knowledge Retention Rate (%)	86.3	65.7	+31.4	< 0.001
Basic Knowledge Retention (%)	89.5	72.3	+23.8	< 0.01
Higher-Order Knowledge Retention (%)	83.2	59.1	+40.8	< 0.001
Knowledge Transfer Success Rate (%)	78.6	61.2	+28.4	< 0.01
Problem-Solving Efficiency (min)	12.3	18.7	-34.2	< 0.001

TABLE VII
COMPARISON OF ADAPTIVE LEARNING EFFECTS FOR LEARNERS OF DIFFERENT AGE GROUPS

Indicator	Younger Group (n=79)	Older Group (n=41)	Significance
Knowledge Mastery Improvement Rate (%)	44.7	35.2	$p < 0.05$
Application Ability Improvement Rate (%)	49.3	43.1	$p < 0.05$
Learning Efficiency (Knowledge per Unit Time)	High	Medium	$p < 0.01$
Knowledge Retention Rate (%)	88.5	82.1	$p < 0.05$
Technology Acceptance (1-5 scale)	4.3	3.6	$p < 0.01$
Satisfaction Rating (1-5 scale)	4.5	3.9	$p < 0.05$

knowledge transfer, the experimental group also demonstrated significantly better abilities than the control group in applying learned knowledge in work scenarios, including a higher transfer success rate and faster problem-solving speed. This may be because large language models can generate learning content and exercises related to actual work, strengthening the connection between knowledge and practice, thereby promoting knowledge transfer.

Multifactor analysis shows that the main factors affecting knowledge retention and transfer include the contextualization degree of learning content ($\beta = 0.42$, $p < 0.01$), the coherence of learning paths ($\beta = 0.38$, $p < 0.01$), and the adequacy of practice opportunities ($\beta = 0.45$, p ¡ 0.001). The adaptive learning system based on large language models has advantages in these aspects, particularly in content contextualization and path coherence.

C. Differential Effects on Different Types of Learners

To deeply understand the impact of adaptive learning paths on different types of learners, this research conducted comparative analyses of different subgroups within the experimental group, focusing on factors such as age, learning style, and technology acceptance.

1) Analysis of Age Factor Influence: The experimental group was divided by age into younger (20-40 years old) and older (41 years and above) groups to compare differences in adaptive learning effects. Results are shown in Table VII.

The data indicates that younger learners generally outperformed older learners on all indicators, with particularly significant differences in learning efficiency and technology acceptance. This suggests that age is indeed a factor affecting the use effectiveness of adaptive learning systems, consistent with Li et al.'s research results on learners' perceived efficacy of language learning with large language models.

Further analysis shows that the main challenges faced by older learners include difficulty in technology adaptation (42.7%), resistance to changing learning habits (37.5%), and insufficient self-directed learning ability (31.2%). These findings suggest that when designing adaptive learning systems for university administrative staff, special attention should be paid to the needs of older learners, providing more user-friendly interfaces and more adequate technical support.

Fig. 6. Comparison of Learning Effects for Learners with Different Learning Styles

2) Analysis of Learning Style Differences: Based on learning style questionnaires, experimental group participants were categorized into visual, auditory, reading, and kinesthetic types to analyze their performance differences in the adaptive learning system. Results are shown in Figure 6.

The data shows that visual learners achieved the best results in the adaptive learning system, followed by reading and auditory types, while kinesthetic learners showed relatively weaker effects. This may be because the current system's content presentation methods are more inclined toward visual and reading materials.

Correlation analysis indicates that the matching degree between adaptive paths and learning styles is an important factor affecting learning outcomes (r = 0.76, p ¡ 0.01). Learning effects significantly improve when the format of system-

TABLE VIII
COMPARISON OF ADAPTIVE LEARNING EFFECTS FOR LEARNERS WITH DIFFERENT TECHNOLOGY ACCEPTANCE

Indicator	High Acceptance (n=68)	Low Acceptance (n=52)	Significance
System Usage Frequency (times/week)	12.7	7.3	$p < 0.001$
Average Usage Duration (min)	37.5	21.8	$p < 0.001$
Knowledge Mastery Improvement Rate (%)	45.8	35.6	$p < 0.01$
Learning Path Adjustment Acceptance (%)	86.3	62.7	$p < 0.001$
Perceived Ease of Use (1-5 scale)	4.2	3.1	$p < 0.01$
Perceived Usefulness (1-5 scale)	4.5	3.7	$p < 0.05$

recommended content aligns with learner preferences. This suggests that large language models need to more precisely identify learning style characteristics and adjust content presentation methods accordingly.

3) Technology Acceptance Analysis: Based on technology acceptance questionnaires, the experimental group was divided into high acceptance (n=68) and low acceptance (n=52) groups to compare differences in learning effects, with results shown in Table VIII.

The data shows that learners with high technology acceptance significantly outperformed those with low technology acceptance in system usage frequency, usage duration, and learning effects. Particularly in terms of learning path adjustment acceptance, the high acceptance group demonstrated stronger adaptability and openness.

Multivariate analysis further reveals that the main factors influencing technology acceptance include perceived ease of use (β = 0.43, $p < 0.01$), perceived usefulness (β = 0.51, $p < 0.001$), and organizational support (β = 0.37, $p < 0.01$). These findings provide guidance for improving the acceptance of adaptive learning systems, namely the need to simultaneously address the user-friendliness of system design, highlight practical value, and provide organizational-level support.

Synthesizing the above analyses, different types of learners show significant differences in adaptive learning paths. Younger learners, visual learners, and those with high technology acceptance benefit more. This finding suggests that when designing adaptive learning systems based on large language models, special attention should be paid to the needs and characteristics of different types of learners, adopting targeted design strategies and support measures to ensure the system is effective for all types of learners.

D. Analysis of System Usage Behavior Patterns

Through analysis of behavioral data of learners in the experimental group, this research identified several typical usage patterns, revealing interaction characteristics between university administrative staff and the adaptive learning system.

1) Learning Time Distribution Characteristics: Analysis of learning time distribution for learners in the experimental group, with results shown in Figure 7.

The data shows that university administrative staff's learning time exhibits a distinct bimodal distribution. On workdays, learning mainly concentrates in the morning (6:30-8:30) and evening (19:00-23:00), with relatively fewer learning activities during work hours. Weekend learning time is more evenly distributed but still mainly in the morning and evening.

This time distribution characteristic reflects the challenge of balancing work and learning for university administrative staff, also indicating that adaptive learning systems need to support fragmented learning and provide appropriate content and difficulty based on learning states at different time periods.

2) Learning Resource Access Patterns: Analyzing resource access records of the experimental group learners identified four main learning resource access patterns, as shown in Table IX.

The task-oriented pattern is the most common, accounting for 42.8%, reflecting university administrative staff's clear goal orientation and pragmatic learning attitude. Notably, different access patterns are significantly correlated with learning outcomes, with deep exploration and task-oriented learners showing more significant improvements in knowledge mastery and skill application ability.

3) Interaction Behavior Analysis: Through interaction log analysis, this research examined the interaction behavior characteristics of learners with the system, with results shown in Table X.

The data shows that learners' interaction behaviors are closely related to their learning characteristics and outcomes. Feedback submission and knowledge quiz participation are the most frequent interaction behaviors, indicating that learners actively participate in self-assessment and system improvement.

Correlation analysis further indicates that the frequency and quality of interaction behaviors are significantly correlated with learning outcomes. Particularly, there is a high positive correlation between practice case attempts and skill application ability (r = 0.81), emphasizing the importance of practical components in university administrative staff training.

Synthesizing the above analyses, university administrative staff demonstrate unique behavior patterns when using adaptive learning systems, including fragmented learning time distribution, goal-oriented resource access, and diverse interaction behaviors. These behavior patterns reflect their characteristics as adult learners and professionals, providing valuable references for system optimization and improvement.

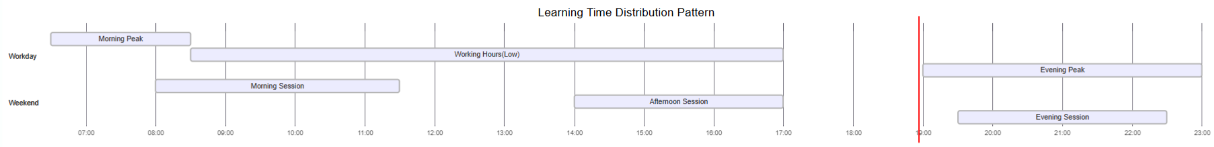

Fig. 7. Learning Time Distribution Patterns of University Administrative Staff

TABLE IX
DISTRIBUTION OF LEARNING RESOURCE ACCESS PATTERNS

Access Pattern	**Proportion (%)**	**Characteristic Description**	**Typical Learner Profile**
Deep Exploration	23.5	Actively explores related resources beyond recommended content, longer learning sessions, frequent interactions	High learning motivation, strong self-directed learning ability, typically with research background
Task-Oriented	42.8	Strictly follows recommended paths, completes core tasks then exits, rarely explores additional content	Clear objectives, limited time, emphasizes practicality, mostly middle management personnel
Selective Acceptance	19.7	Filters recommended content, only learns parts perceived as interesting or useful	Has clear learning intentions, strong self-judgment ability, mostly senior personnel
Superficial Engagement	14.0	Short learning sessions, jumps between content, rarely completes a full module	Insufficient learning motivation, high time pressure, or unfamiliarity with the system

TABLE X
ANALYSIS OF SYSTEM INTERACTION BEHAVIOR CHARACTERISTICS

Interaction Behavior	**Frequency (avg)**	**Related Factors**	**Effect Correlation**
Content Adjustment Requests	3.5 times/week	Positively correlated with learner autonomy (r = 0.65)	Positively correlated with learning satisfaction (r = 0.58)
Feedback Submission	4.2 times/week	Positively correlated with system improvement perception (r = 0.72)	Positively correlated with path precision (r = 0.63)
Knowledge Quiz Participation	5.8 times/week	Positively correlated with goal orientation (r = 0.69)	Positively correlated with knowledge mastery (r = 0.74)
Practice Case Attempts	2.7 times/week	Positively correlated with application orientation (r = 0.77)	Positively correlated with skill application ability (r = 0.81)
Learning Record Review	3.9 times/week	Positively correlated with self-monitoring tendency (r = 0.61)	Positively correlated with learning strategy adjustment (r = 0.57)

V. DISCUSSION AND IMPLICATIONS

A. *Theoretical Significance of Research Results*

The empirical results of this research bring the following theoretical implications for the application of large language models in education and adaptive learning theory:

First, the research results indicate that large language models demonstrate good application potential in knowledge tracking and path generation, expanding the technical perspective of knowledge tracking theory. Compared to traditional rule-based or statistical knowledge tracking methods, large language models demonstrate greater flexibility and semantic understanding capabilities, especially in processing complex knowledge states and unstructured learning behavior data. This finding provides a new technical path for knowledge tracking theory and a theoretical foundation for adaptive learning system design.

Second, the research reveals the differential impact of adaptive learning paths on different types of learners, enriching the empirical foundation of adult learning theory. Results show that factors such as age, learning style, and technology acceptance significantly influence adaptive learning effects. Particularly, the research found significant effects of adaptive learning systems in enhancing university administrative staff's practical abilities and knowledge transfer, supporting situational learning theory and application-oriented principles in adult learning.

Third, the adaptive learning theoretical framework based on large language models constructed in this research provides a new theoretical perspective for the integration of educational technology and artificial intelligence. This framework integrates four dimensions: learner modeling, knowledge representation, path generation, and effect evaluation, forming a systematic analytical framework. Specifically, the research emphasizes large language models' contextual understanding and reasoning capabilities when handling complex educational scenarios, providing new theoretical guidance for adaptive learning system design.

Finally, the research results have important implications for understanding the interaction mechanisms between technology and learning processes. By analyzing learners' time distribution, resource access, and interaction behavior patterns, this research reveals how technology influences and shapes learning behaviors. These findings provide empirical foundations for theoretical research on technology-supported learning, contributing to a deeper understanding of learning dynamics in digital environments.

B. Design Implications for Practice

The results of this research provide the following practical implications for designing adaptive learning systems for university administrative staff:

First, differentiated design for different types of learners is crucial. Research shows that learners of different ages, learning styles, and technology acceptance levels demonstrate significant differences in their performance in adaptive systems. Therefore, system design should consider multidimensional personalization strategies, such as providing more user-friendly interfaces and more adequate guidance for older learners, diverse content presentation methods for learners with different learning styles, and progressive technical adaptation support for learners with low technology acceptance.

Second, research results show that the integration of learning content with work practice is an important factor affecting learning outcomes (r = 0.78, p ¡ 0.01). The research found that the experimental group's advantages in application ability and knowledge transfer are particularly significant. Therefore, system design should emphasize the design of practical components, such as case analyses, role-playing, and problem-solving tasks based on real work scenarios, and generate personalized content related to learners' work backgrounds through large language models, enhancing the practicality and transferability of knowledge.

Third, function design supporting fragmented learning and self-directed learning is necessary. Behavioral data analysis shows that university administrative staff's learning exhibits fragmented characteristics and multiple resource access patterns. Therefore, the system should provide flexible learning unit division, progress saving, and intelligent recommendation functions, supporting learning needs in different scenarios. Simultaneously, self-directed learning support tools should be designed, such as learning plan formulation, progress tracking, and self-assessment functions, enhancing learners' autonomy and sense of control.

Fourth, interaction design should focus on promoting deep engagement and feedback loops. Research shows that the frequency and quality of interaction behaviors are closely related to learning outcomes. Therefore, the system should design diverse interaction mechanisms, such as targeted questions, timely feedback, and encouraging evaluations, generating personalized, contextual interaction content through large language models, enhancing learners' engagement and satisfaction. At the same time, effective feedback collection and analysis mechanisms should be established, continuously optimizing learning paths and content recommendations.

Finally, organizational-level support and integration should not be overlooked. Research finds that technology acceptance and usage effectiveness are significantly influenced by organizational support. Therefore, during system implementation, corresponding organizational support measures should be provided, such as adequate training and technical support, establishing incentive mechanisms, and incorporating adaptive learning into organizational development strategies, creating a favorable application environment.

C. Research Limitations and Future Research Directions

Despite its contributions, this research presents several limitations that indicate future research trajectories:

First, the brief experimental duration impedes evaluation of long-term effects. Although two-week follow-up tests were conducted, capability development requires extended observation. Future research should employ longitudinal designs to assess the sustained impact on career progression and organizational effectiveness.

Second, sample limitations in size and geographical distribution potentially compromise result generalizability. Subsequent studies should expand sampling across diverse regions and institutional types to enhance representativeness and broader applicability.

Third, while technical implementation and learning outcomes were thoroughly examined, ethical considerations regarding large language model applications in education received insufficient attention. Future work must develop robust ethical frameworks and privacy protection mechanisms to ensure responsible technology deployment.

Fourth, the research utilized general-purpose language models with minimal domain-specific optimization. Future investigations should explore targeted fine-tuning incorporating administrative expertise and educational theory to enhance model performance in specialized contexts.

Finally, assessment relied primarily on conventional learning metrics without adequately exploring innovative evaluation approaches. Future research should develop comprehensive frameworks incorporating process-based assessment, capability development trajectories, and socio-emotional outcomes to thoroughly evaluate adaptive learning's multidimensional impact. Large language model-based adaptive learning for university administrative staff remains a promising research direction. Continued technological advancement and deeper educational applications will likely yield significant breakthroughs in theory, technology, implementation, and assessment methodologies, ultimately enhancing professional development and institutional governance capabilities.

VI. Conclusion

This research explores innovative methods for constructing adaptive learning paths for university administrative staff based on large language models. Through theoretical analysis, system design, and empirical evaluation, the following main conclusions are drawn:

First, within the scope of this research experiment, large language models demonstrate technical potential in supporting the construction of adaptive learning paths for university administrative staff. Research shows that large language models exhibit significant advantages in knowledge tracking, path generation, and content recommendation, particularly in handling complex knowledge states and personalized needs. Compared to traditional methods, adaptive learning systems based on large language models can generate more precise, more personalized learning paths, adapting to university administrative staff's diverse learning needs and characteristics.

Second, adaptive learning paths based on large language models can effectively enhance learning outcomes for university administrative staff. Experimental results show that compared to traditional fixed learning paths, adaptive learning paths reduce learning time by approximately 20%, improve knowledge mastery and application ability by approximately 20%, and enhance knowledge retention by approximately 31%. These improvements are reflected not only in short-term learning effects but also in long-term knowledge retention and practical work application, holding important value for university administrative staff's professional development.

Third, different types of learners benefit to varying degrees from adaptive learning paths. Research finds that younger learners, visual learners, and those with high technology acceptance benefit more significantly. This indicates that adaptive learning system design needs to consider the characteristics of different learners, ensuring various learner types benefit effectively through differentiated design and support strategies.

Fourth, university administrative staff's learning behaviors exhibit unique patterns. Research reveals their fragmented learning time distribution, goal-oriented resource access, and diverse interaction behaviors. These patterns align with adult learning theory, reflecting their characteristics as adult professionals and providing important references for adaptive learning system design.

This research confirms the feasibility and effectiveness of large language models in constructing adaptive learning paths, providing a new technical approach and methodological framework for the intelligent upgrade of university administrative staff training systems. At the same time, the research also points out current challenges and future development directions, including long-term effect evaluation, sample expansion, ethical and privacy considerations, domain-specific optimization, and assessment method innovation. Future research should continue to delve deeper in these directions, further enhancing the effectiveness and value of adaptive learning systems based on large language models.

References

[1] A. Chowdhery et al., "Palm: Scaling language modeling with pathways," Journal of Machine Learning Research, vol. 24, no. 240, pp. 1-113, 2023.
[2] G. Abdelrahman, Q. Wang, and B. Nunes, "Knowledge tracing: A survey," Comput. Surveys, vol. 55, no. 11, pp. 1-37, 2023.
[3] I. C. Peláez-Sánchez, D. Velarde-Camaqui, and L. D. Glasserman-Morales, "The impact of large language models on higher education: exploring the connection between AI and Education 4.0," Front. Educ., vol. 9, 1392091, Jun. 2024.
[4] M. Wang, D. Zhang, J. Zhu, and H. Gu, "Effects of Incorporating a Large Language Model-Based Adaptive Mechanism Into Contextual Games on Students' Academic Performance, Flow Experience, Cognitive Load and Behavioral Patterns," SAGE Journals, vol. 9, no. 4, pp. 123-145, 2025.
[5] W. Strielkowski, V. Grebennikova, A. Lisovskiy, G. Rakhimova, and T. Vasileva, "AI-driven adaptive learning for sustainable educational transformation," Sustainable Development, 2024.
[6] C. Ng and Y. Fung, "Educational Personalized Learning Path Planning with Large Language Models," arXiv preprint arXiv:2407.11773, 2024.
[7] K. Bayly-Castaneda, M-S. Ramirez-Montoya, and A. Morita-Alexander, "Crafting personalized learning paths with AI for lifelong learning: a systematic literature review," Front. Educ., vol. 9, 1424386, Aug. 2024.
[8] C. Sun, S. Huang, B. Sun, and S. Chu, "Personalized learning path planning for higher education based on deep generative models and quantum machine learning: a multimodal learning analysis method integrating transformer, adversarial training and quantum state classification," Discover Artificial Intelligence, vol. 5, no. 1, p. 29, 2025.
[9] H. Xu, W. Gan, Z. Qi, J. Wu, and P. S. Yu, "Large language models for education: A survey," arXiv preprint arXiv:2405.13001, 2024.
[10] S. Sharma, P. Mittal, M. Kumar, and V. Bhardwaj, "The role of large language models in personalized learning: a systematic review of educational impact," Discover Sustainability, vol. 6, no. 1, pp. 1-24, 2025.
[11] S. Wang, T. Xu, H. Li, C. Zhang, J. Liang, J. Tang, and Q. Wen, "Large language models for education: A survey and outlook," arXiv preprint arXiv:2403.18105, 2024.
[12] J. Zheng, C. Shi, X. Cai, Q. Li, D. Zhang, C. Li, and Q. Ma, "Lifelong Learning of Large Language Model based Agents: A Roadmap," arXiv preprint arXiv:2501.07278, 2025.
[13] B. Jiang, X. Li, S. Yang, Y. Kong, W. Cheng, C. Hao, and Q. Lin, "Data-driven personalized learning path planning based on cognitive diagnostic assessments in MOOCs," Applied Sciences, vol. 12, no. 8, p. 3982, 2022.
[14] M. Kabir and F. Lin, "An LLM-Powered Adaptive Practicing System," in AIED 2023 workshop on Empowering Education with LLMs, 2023.
[15] R. Li, Y. Wang, C. Zheng, Y. H. Jiang, and B. Jiang, "Generating contextualized mathematics multiple-choice questions utilizing large language models," in International Conference on Artificial Intelligence in Education, Cham: Springer Nature Switzerland, pp. 494-501, 2024.
[16] Q. Li, L. Fu, W. Zhang, X. Chen, J. Yu, W. Xia, and Y. Yu, "Adapting large language models for education: Foundational capabilities, potentials, and challenges," arXiv preprint arXiv:2401.08664, 2023.
[17] Y. Sharma, A. Suri, R. Sijariya, and L. Jindal, "Role of education 4.0 in innovative curriculum practices and digital literacy–A bibliometric approach," E-Learning and Digital Media, vol. 22, no. 1, pp. 1-32, 2025.
[18] L. Pretorius, "An active learning intervention for in-service teachers: self-determination theory, heutagogy, neuroeducation and the (altered) flipped classroom in practice," Curriculum Perspectives, pp. 1-14, 2025.
[19] K. Li, L. Lun, and P. Hu, "Exploring student perceptions of language learning affordances of Large Language Models: AQ methodology study," Education and Information Technologies, pp. 1-21, 2025.
[20] H. Huang, "Promoting students' creative and design thinking with generative AI-supported co-regulated learning," Educational Technology & Society, vol. 27, no. 4, pp. 487-502, 2024.
[21] C. G. Demartini, L. Sciascia, A. Bosso, and F. Manuri, "Artificial intelligence bringing improvements to adaptive learning in education: A case study," Sustainability, vol. 16, no. 3, p. 1347, 2024.
[22] W. Chen, Z. Shen, Y. Pan, K. Tan, and C. Wang, "Applying machine learning algorithm to optimize personalized education recommendation system," Journal of Theory and Practice of Engineering Science, vol. 4, no. 01, pp. 101-108, 2024.
[23] O. B. Joseph and N. C. Uzondu, "Integrating AI and Machine Learning in STEM education: Challenges and opportunities," Computer Science & IT Research Journal, vol. 5, no. 8, pp. 1732-1750, 2024.