International Journal of Information Technology and Web Engineering
Volume 19 • Issue 1

Exploration of College Students' Learning Adaptability Under the Background of Wisdom Education

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ABSTRACT

This article takes college students' learning adaptability as the research object, adopts B/S structure to develop a learning adaptive platform, designs a learner data model, a learning style model, a learning resource presentation module, and an ability level test module; tests the platform through simulated data; and analyzes college students' learning style, knowledge level and learner collaboration level. The results show that college students' learning adaptation has the characteristics of flexibility, individuality, initiative, and reflection. A self-adaptive learning platform can understand its learning state and effect through learning evaluation, adjust its learning strategies and methods in time, and help college students better understand and master knowledge. The research results provide theoretical data support for the exploration of college students' learning adaptability under the background of wisdom education.

KEYWORDS

Ability Level, Adaptive Platform, College Students, Wisdom Education

INTRODUCTION

With the rapid development of internet+, big data, and artificial intelligence technology, the traditional education industry is showing the characteristics of "wisdom." By means of information technology, intelligent technology is applied to education to improve the quality and efficiency of education (Nevzorova et al., 2023). The core of wisdom education is to provide personalized learning resources and teaching methods according to students' individual characteristics and needs, so as to promote students' learning interest and initiative (Yuniata et al., 2023). With the rapid development of smart education, it is very important for college students to learn adaptively (Clunis, 2023). In traditional education, teachers are the main focus, and students passively accept knowledge (Cheung et al., 2021). However, under smart education, students get rich educational resources and information, and they can realize personalized learning according to their own interests, hobbies, and learning styles (Keskitalo & Ruokamo, 2021). This adaptive learning method stimulates students' learning motivation and potential and improves learning effect. Therefore, under wisdom education, the

DOI: 10.4018/IJITWE.336486
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study of college students' learning adaptability is of great significance (Ivemark & Ambrose, 2021). This paper takes college students' learning adaptability as the research object; adopts B/S structure to develop an adaptive learning platform; designs a learner data model, a learning style model, a learning resource presentation module, and an ability level testing module; tests the platform through simulated data; analyzes college students' learning style, knowledge level, and learner collaboration level; and provides theoretical data support for exploring college students' learning adaptability under the background of smart education.

LITERATURE REVIEW

Some research results have been presented on college students' learning adaptability under the background of wisdom education. Zhai et al. (2021) studied the construction of intelligent learning environments. By deeply integrating education and information technology, an intelligent learning environment was established based on information technology. Taking the learning environment as the research object, the system model and function model of the intelligent learning environment were presented, which formed the research results of intelligent education development and led to the development model of future learning environments (Zhai et al., 2021). Stevens et al. (2021) studied the characteristics of intelligent learning. With the rapid development of information technology and the new changes in learning environments, learning methods and needs have higher requirements. The intelligent learning environment promotes the generation of intelligent learning, which is student-centered, supported by new technologies, meets the individualized learning needs of different students, cultivates innovative thinking abilities, promotes the generation and development of students' wisdom, and realizes students' individualized development (Stevens et al., 2021). Al-Adwan et al. (2023) studied the adaptive online teaching method. Through course learning and content promotion, the course content was adjusted according to the needs of scholars, and a nonlinear online teaching method was customized based on the knowledge learned by scholars. Learning adaptability was embedded in the online teaching method, and it was concluded that learners decided the online learning content by interacting with the learned content, which was automatically and dynamically completed in the interaction, thus realizing a personalized learning experience (Al-Adwan et al., 2023). Jeong (2022) proposed the adaptive learning method and claimed that adaptive learning runs through the whole online learning process; intelligently records and transmits learning information with the help of situation and online technology; accurately grasps the learning situation of each learner; and analyzes the relationship between each student's learning process and his ability, learning environment, and learning situation (Jeong, 2022). Sobocinski et al. (2022) studied the learning adaptability of college students, improved the learning effect by establishing learning adaptability, and provided personalized learning resources and teaching programs according to the learning characteristics and needs of each student to better meet the learning needs of each student. They then claimed that by choosing learning resources independently and adjusting learning strategies synchronously, students can better adapt to the learning environment and challenges they face and constantly cultivate their autonomous learning ability. Finally, through learning adaptability, students can actively participate in the learning process, improve their learning fun and motivation, persist in learning better, and achieve excellent results (Sobocinski et al., 2022).

RELATED MATERIALS AND METHODS

Objectives

College students' learning adaptation refers to the flexible adjustment of learning strategies and methods according to their own characteristics and needs in the learning process to adapt to different learning environments and tasks. Emphasizing students' initiative and autonomy through this learning method can help students better adapt to the requirements of college learning and improve learning effects (Xhelili et al., 2021). The core of college students' learning adaptation is students' own cognition and reflection on learning. Students need to know their own learning characteristics and learning needs, make clear their learning goals, and make corresponding learning plans according to those goals. In the process of learning, students need to constantly reflect on their learning effects and adjust their learning strategies and methods to meet the requirements of different disciplines, different teaching methods, and different learning environments (da Silva et al., 2021).

The characteristics of college students' learning adaptation include:

- **Flexibility:** College students' learning adaptation emphasizes that students can flexibly adjust their learning strategies and methods according to different situations and needs. Students can choose appropriate learning methods and learning resources according to their interests and abilities to meet their learning needs.
- **Individualization:** College students pay attention to giving full play to their personality characteristics and advantages in learning self-adaptation. Students can choose their own learning methods and learning resources according to their learning style and learning ability, so as to improve their learning effect.
- **Initiative:** College students' learning adaptation emphasizes their initiative. Students need to actively understand their learning needs and goals and actively adjust learning strategies and methods to meet the requirements of different learning environments and tasks.
- **Reflectivity:** College students' learning adaptability requires students to constantly reflect on their learning effect and learning process. Students need to adjust their learning strategies and methods according to their own learning progress and learning effect in order to improve their learning effect (Singh et al., 2021).

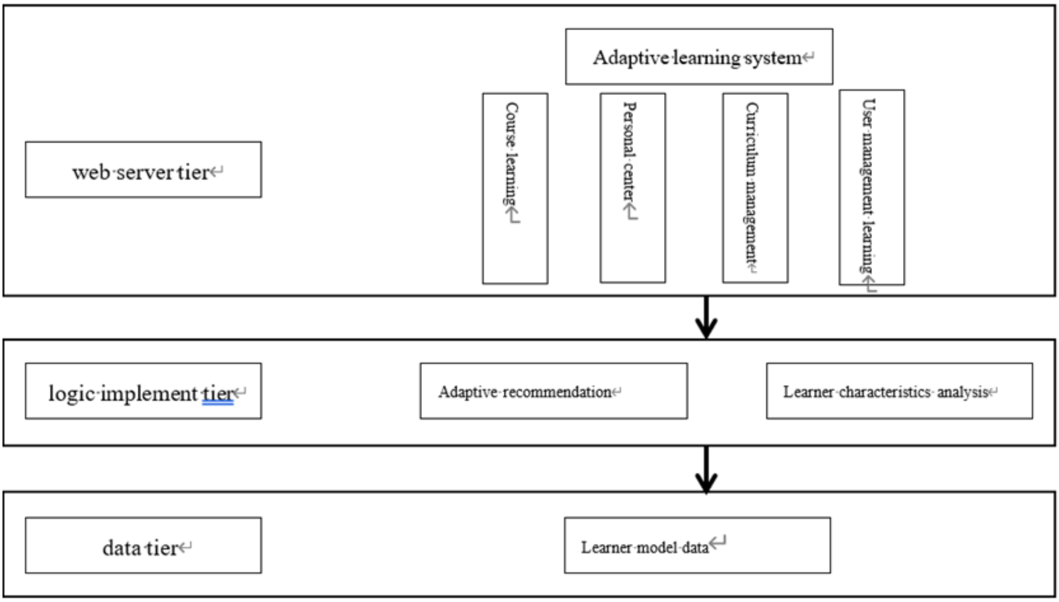
The importance of college students' learning adaptation lies in helping students better adapt to the requirements of university study and improving the learning effect. Compared with the middle school stage, university study has changed greatly; the depth and breadth of subject knowledge have increased and the diversification of teaching methods and the complexity of learning tasks have created higher requirements for students (Takács et al., 2021). Through learning self-adaptation, students can flexibly adjust their learning strategies and methods according to their own characteristics and needs and improve their learning effect. At the same time, learning adaptation also cultivates students' autonomous learning abilities and problem-solving abilities, laying a solid foundation for their future study and work (Solovov & Menshikova, 2023).

In order to implement college students' learning adaptation, students need to have certain learning abilities and learning skills. First of all, students need to have self-management abilities, including time management, goal setting, and plan making, to ensure the effectiveness of learning. Secondly, students need to have the ability to solve problems, including analyzing problems, finding solutions, and evaluating effects, so as to cope with the difficulties and challenges in the learning process. In addition, students also need to have the ability to acquire and process information, including effectively acquiring learning resources and information and screening and sorting information, so as to improve the learning effect (Li et al., 2021).

Design of Adaptive Learning Platform

In this paper, the B/S development structure is adopted and the data layer, business logic layer, and Web layer are set up to establish the adaptive learning system. Figure 1 is the structure diagram of the adaptive learning system. The adaptive learning system includes course learning, course management, personal center, and user management, and the system can be viewed and operated through the Web. The business logic layer mainly realizes the analysis of college students' learning characteristics and

Figure 1. Structure diagram of adaptive learning system



the recommendation of adaptive knowledge; the data layer is mainly used to store the learning model data of college students (Alexa et al., 2022).

College students' adaptive learning platform is a platform to realize autonomous learning. The statistics of college students' personal information and interest preferences can better analyze the learning characteristics of college students, make learning more private and safer, and facilitate teachers to analyze the learning data of college students (Kozlova & Pikhart, 2021). When freshmen enter the adaptive learning platform, they need to register their accounts and fill in their names, genders, student numbers, grades, contact information, hobbies, and knowledge. The platform automatically judges the validity of the information and stores it in the background database. The information input model of college students established in this paper mainly includes student description (Table 1), interest preference (Table 2), learning style (Table 3), and cognitive state (Table 4). Figure 2 shows the flow chart of college students' information input module.

The learning style module is the main module of adaptive learning platform, which is composed of F-S learning style scale. By analyzing the scores of college students on 50 multiple-choice questions,

Table 1. Data of college students' descriptions

Field	Data type	Field description
account number	int	Student ID, unique identification code
user name	string	student's name
password	string	Login password
gender	string	
grade	string	
Contact ways	string	

Table 2. Data of college students' interest preference

Field	Data type	Field description
Media type preference	string	Text, video
Author preference	string	
Knowledge preference	string	

Table 3. Data of college students' learning style

Field	Data type	Field description
account number	int	
information input	string	{a, 3a, 5a, 7a, 9a, 11a, 11b, 9b, 5b, 3b, b}
process	string	
perception	string	
understand	string	

Table 4. Data of college students' cognitive status

Field	Data type	Field description
account number	int	
Knowledge point number	int	Knowledge point number
Score	int	Score of this knowledge point
Test status	boolean	Ture/false
Ability level	int	{1, 2, 3}
Learning state	boolean	Ture/false
Access status	boolean	Ture/false
Master the state	boolean	Ture/false

the scores and analysis results are stored in the background database. After the user logs in to the adaptive learning platform, the system will automatically judge whether the college students have completed the learning style test. When the system judges that the test has not been completed, it will jump to the learning style test interface, requiring the college students to complete the test within one hour. When the user finishes submitting the questions, the system will display the learning style of the college students and store it in the database. Figure 3 shows the flow logic diagram of college students' learning style module.

As the core module of the adaptive learning platform, the learning resource presentation module mainly includes learning resources, knowledge points, and learning activities. College students learn the main knowledge through the learning resource presentation module, which presents the corresponding media learning resources to learners (Won et al., 2021). At the same time, after completing the learning of a knowledge point, the system pushes the next suitable knowledge point to scholars according to college students' completion, which has different requirements and habits for the order arrangement of learning activities (Wang et al., 2023). In

Figure 2. Logic diagram of college students' information input process

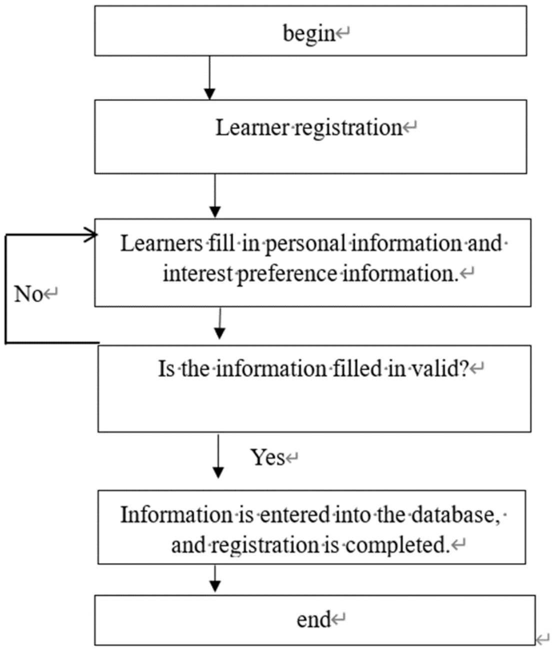
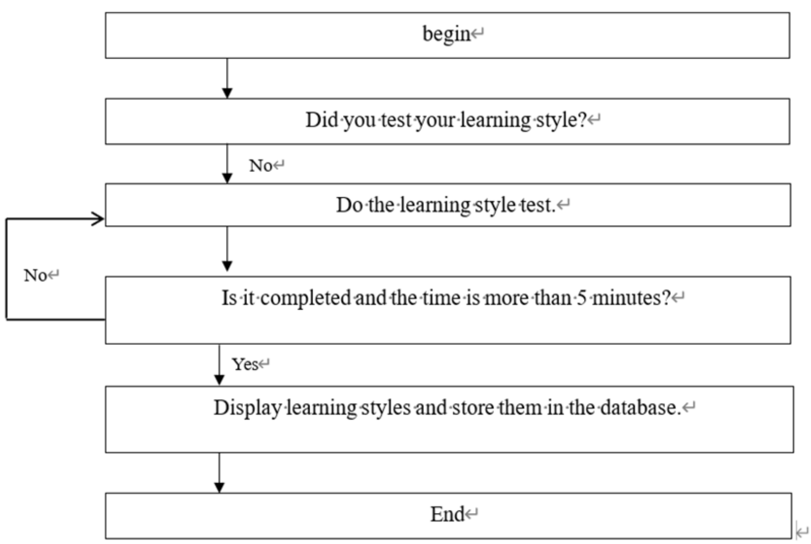


Figure 3. Flow logic diagram of college students' learning style module



this paper, the learning activities of the adaptive learning platform are divided into six parts: overview, resource learning, discussion, practical operation, problem-solving, and summary. Users can view the learning resources of similar relationships and share, download, and like them at the same time (Mohammed et al., 2022).

The ability level test module is the main way to test the knowledge level of college students. The module is mainly composed of knowledge points and a test question bank, and each knowledge point contains 20 test questions with different difficulties and types (Yang, 2022). Through the system test, the actual scores of college students on the ability level of each knowledge point can be calculated, and by comparing it with the reference scores of this knowledge point test question, the ability level grade can be obtained (Li, 2022). After completing the study of a knowledge point, college students enter the test activities, complete the test questions given by the system in turn, and click the hand-in button. The system judges whether the completion time is more than 5 minutes to ensure the validity of the answer and, finally, the system judges the test scores (Chen, 2020).

RESULTS AND ANALYSIS

In order to ensure the accuracy and reliability of the platform, the user's behavior is simulated by simulating a large number of user data before the platform is officially used. In the smart education industry, the academic performance of college students generally presents a normal distribution, and the system randomly generates normal distribution scores to simulate the scores of college students in knowledge test questions.

After collecting the basic personal information of college students, this paper simulates and generates the scores of 100 users based on the normal distribution of students' scores in the same knowledge point. According to the adaptive recommendation, not all users will learn every knowledge point, and only the required part is used for the generated data. Figure 4 presents the user scores of this part.

This paper tests the recommendation of college students' learning styles, mainly four different learning styles. This paper tests the recommendation of college students' learning styles, mainly four different learning styles, through examples so as to test the effect of users' learning styles.

- **The first learning style:** Visual learning style, click to start learning, expect to display learning resources of video and picture types, and actually output them as learning resources of video and picture types.
- **The second learning style:** Text-based learning style. Click Start Learning, expecting to display text-based learning resources, and the actual output is to display text-based learning resources.
- **The third learning style:** Active learning style. Click to start learning. It is expected that the order of learning activities will be: overview, resource learning, discussion, practice, discussion,

Figure 4. Partial user performance chart

	K1	K2	K3	K4	K5	K6	K7	K8
S1	79	88	82	91	77	84	84	82
S2	82	83	92	78	80	77	91	85
S3	85	88	81	71	81	90	88	85
S4	74	89	92	85	85	87	91	89
S5	83	87	88	81	80	81	84	84
S6	91	78	84	98	86	88	83	83
S7	86	90	85	90	78	78	89	87
S8	92	91	84	82	81	89	91	88
S9	93	87	93	92	91	80	78	84

problem solving and summary, while the order of actual output learning activities will be: overview, resource learning, practice, discussion, problem solving and summary.

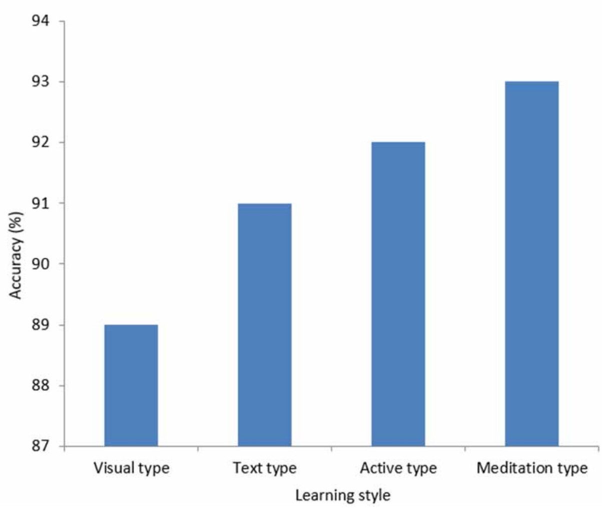
- **The fourth learning style:** Contemplative learning style. Click to start learning. It is expected that the order of learning activities will be overview, resource learning, practical exercise, problem solving, discussion and summary, while the order of actual output learning activities will be overview, resource learning, practical exercise, problem solving, discussion and summary.

Figure 5 shows the accuracy of different learning styles. On the whole, the expected output of each learning style is basically consistent with the actual output, and the platform test accuracy is high.

This paper tests the recommendation of college students' knowledge level and checks whether the recommendation based on knowledge level is normal through the user's knowledge point test. The results are as follows:

Example 1 - Input: User A scored 77 points for completing the first knowledge point. Expected output: not up to standard, unable to learn the next knowledge point, re-recommend learning resources. Actual output: it is not up to standard, so it is impossible to learn the next knowledge point, and learn the knowledge point again.
Example 2 - Input: User B scored 84 points for completing the first knowledge point. Expected output: the results are up to standard, and it is recommended to start the second knowledge point study. Actual output: the results are up to standard, and it is recommended to continue learning the second knowledge point.
Example 3 - Input: F User's score for completing the first knowledge point is 96 points. Expected output: the results are up to standard, and it is recommended to learn the second and third knowledge points of the same type. Actual output: up to standard, it is recommended to continue learning the second and third knowledge points.
Example 4 - Input/Action: User A scored 88 points for completing the first knowledge point again. Expected output: the results are up to standard, and it is recommended to continue learning the second knowledge point. Actual output: the results are up to standard, and it is recommended to learn the second knowledge point.

Figure 5. Accuracy of different learning styles tests



Example 5 - Input/Action: The scores of users who completed the first knowledge point three times were 75, 76 and 78 respectively. Expected output: this knowledge point has reached the highest learning times, and you can continue to learn the second knowledge point. Actual output: this knowledge point has reached the maximum number of learning times, and it is recommended to learn the second knowledge point later.

This paper tests the collaborative filtering recommendation of college students and checks whether the collaborative filtering recommendation based on learners is normal through the collaborative filtering recommendation of college students with similar learning behaviors. Example 1 showed the following:

- **Input:** A and B praised, shared, and downloaded the first knowledge point, and user B chose learning resource 1 when learning the second knowledge point.
- **Expected output:** When learning the second knowledge point, learning resource 1 appears.
- **Actual output:** When learning the second knowledge point, learning resource 1 appears, and the status is passed.

Under the background of wisdom education, college students use all kinds of intelligent tools and resources to explore learning adaptability more independently and improve learning effect and satisfaction. With the adaptive learning platform proposed in this paper, college students can choose their own learning strategies, such as active learning, cooperative learning, and inquiry learning. They can make use of various intelligent learning resources, such as online courses, learning platforms, and virtual laboratories, to explore their learning adaptability. Through learning evaluation, college students can understand their learning status and effects, adjust their learning strategies and methods in time, and better understand and master knowledge.

CONCLUSION

With the rapid development of educational informatization and intelligent technology, intelligent teaching methods promote the development of college students' learning adaptability. This paper takes college students' learning adaptability as the research object; adopts B/S structure to develop an adaptive learning platform; designs a learner data model, a learning style model, a learning resource presentation module, and an ability level testing module; tests the platform through simulated data; analyzes college students' learning style, knowledge level, and learner collaboration level; and provides theoretical data support for exploring college students' learning adaptability under the background of smart education. The main results of this study include the following:

- College students' learning adaptation has the characteristics of flexibility, individuality, initiative, and reflection. A B/S development structure is adopted, and a learning adaptation platform is established by setting up a data layer, a business logic layer and a Web layer, which consists of a college student information input module, a learning style module and a learning resource presentation module. The information input model of college students mainly includes students' description, interest preference, learning style, and cognitive state. The learning style module is composed of F-S learning style scale, which analyzes the scores of college students in 50 multiple-choice questions. The learning resource presentation module mainly includes learning resources, knowledge points, and learning activities, which are mainly divided into six parts: overview, resource learning, discussion, practical exercise, problem solving, and summary. The ability level test module is composed of knowledge points and a test question bank, and the students' scores on each item are calculated.

- By testing the recommendation of college students' learning styles, four different learning styles, namely visual, literal, active, and contemplative, are tested, and it is concluded that the expected output of each learning style is basically consistent with the actual output, and the test accuracy is high. By testing the knowledge level recommendation of college students and completing the knowledge point test by users, it is confirmed that the knowledge level recommendation of the platform is accurate. By testing the collaborative filtering recommendation of college students, it is concluded that the result of collaborative filtering recommendation based on learners is normal. The adaptive learning platform enables college students to explore learning adaptability, understand their learning state and effect through learning evaluation, adjust their learning strategies and methods in time, and better understand and master knowledge.

This study provides more theoretical support and practical guidance for the learning adaptability of college students in the context of smart education and promotes the widespread application and in-depth development of smart education technology in teaching practice.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

FUNDING STATEMENT

This work was not supported by any funds.

ACKNOWLEDGMENT

The authors would like to show sincere thanks to those who have contributed to this research.

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