

Research on Intelligent Question-Answering Assistant for New Energy Vehicles Based on Heuristic Interaction

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Abstract: Against the backdrop of artificial intelligence, students majoring in new energy vehicle technology at higher vocational colleges often rely on AI tools due to insufficient problem-solving abilities, which easily leads to dependency addiction and mental inertia. Moreover, existing AI tools lack emotional interaction and guidance on professional literacy, making them unable to meet the needs of education. To address this, an intelligent question-answering assistant for this major is constructed. It innovatively adopts heuristic interaction simulating teacher-student communication to stimulate independent exploration, integrates emotional recognition and feedback mechanisms, and incorporates professional spirit and ideological-political elements to realize whole-process education. Verified through analysis of its design ideas, effect comparisons, and simulated teaching cases, it can effectively improve students' problem-solving abilities and cultivate their professional literacy, providing a new paradigm for the deep integration of vocational education and artificial intelligence.

Keywords: Intelligent Question-Answering Assistant; Heuristic Interaction; Multimodal Knowledge Base; Emotional Care; New Energy Vehicles.

1. Introduction

Currently, China attaches great importance to the development of artificial intelligence (AI), which is penetrating into all walks of life at an unprecedented speed and scope. The country has been continuously promoting the in-depth integration of AI in the field of education, introducing a series of policies and measures to accelerate the strategic layout of AI in aspects such as teacher resources, teaching, and campus [1,2]. Meanwhile, against the backdrop of the increasingly severe global energy crisis, environmental pollution issues, and the industrial era of Industry 4.0, the new energy vehicle technology industry serves as an important approach to addressing these problems. With the continuous expansion of the new energy vehicle technology market scale, the demand for innovative talents is also growing accordingly. This has brought unprecedented development opportunities for the cultivation of new energy vehicle technology talents in higher vocational colleges.

In recent years, the breakthrough progress in generative artificial intelligence (GenAI) large-model technology has propelled intelligent question-answering systems into a new stage of cognitive intelligence. Training models represented by GPT-4, with hundreds of billions of parameters and multimodal training [3,4], have achieved a revolutionary improvement in language understanding and generation capabilities. However, general models still have significant limitations in terms of the timeliness and accuracy of knowledge in professional fields, and the reasoning and planning capabilities of models such as GPT-4 have also been questioned [5]. Deepseek, a representative of advanced domestic large models, can quickly draw correct conclusions for structured problems, with a clear and concise logical deduction process, and can summarize the common factors behind common phenomena [6]. This in-depth thinking mode has laid a solid foundation for the integration of intelligent question-answering assistants with higher education.

2. Analysis of the Current Situation of Students and Ai Application in The New Energy Vehicle Technology Major of Higher Vocational Colleges

The accelerating iteration of AI technology and the fundamental conflicts between traditional vocational education models are centrally reflected in the structural contradictions in the paradigm of knowledge production. Within the framework of technological determinism, the knowledge transmission logic adhered to by the vocational education system stands in deep paradigmatic opposition to the scene-driven, dynamically evolving characteristics of knowledge generation inherent in AI technology [7]. As the core hub of knowledge transmission, vocational education teachers have a weak understanding of AI application scenarios, and the update cycle of vocational education courses lags far behind the generational replacement speed of AI technology [8]. So far, foreign countries have developed large AI education models specifically for the field of education, such as Khanmigo and ChatGPT Edu, which address various educational scenario tasks. These serve as teaching aids to support students' personalized question-answering assistant [9]. In China, however, except for a few question-answering systems developed for teaching [10-14], the AI software commonly used by students in the teaching process are mostly general AI software, such as Doubao and Deepseek domestically. The use of non-professional general AI software in higher vocational teaching still has significant drawbacks and risks, which have gradually emerged.

2.1. Obstacles in Knowledge Integration and Dilemma of Shallow Acquisition

To systematically cultivate talents in the new energy vehicle technology major, higher vocational colleges divide professional knowledge into multiple modules, such as basic compulsory courses, core courses, and specialized elective

courses. These modular courses exhibit knowledge overlap, logical connections, and progressive articulation, while maintaining relatively independent knowledge boundaries. In the process of deepening professional learning, such a modular structure easily causes interdisciplinary knowledge boundaries to evolve into cognitive barriers. As a result, although students can master modular knowledge, they generally face cognitive obstacles in knowledge integration, which is particularly prominent in highly comprehensive majors. Consequently, students' abilities in knowledge integration and application are restricted, making it difficult for them to accurately identify the core crux of encountered problems.

New energy vehicle technology itself is a highly integrated, interdisciplinary field. Students' fault diagnosis of vehicles often requires finding connections from knowledge points across different courses for comprehensive diagnosis. When students encounter professional problems and attempt to solve them independently, they usually adopt the following two approaches:

First, the traditional retrieval method. For loosely coupled problem retrieval systems, this method can only provide retrieval results with high similarity, resulting in a problem-solving process characterized by high randomness and low efficiency. When this method fails to solve problems efficiently, students turn to mature AI software for knowledge acquisition. Although such software has strong networked retrieval capabilities, it directly copies results from online searches, often only providing superficial and simplified answers and failing to guide students in systematic thinking.

Over time, students get used to acquiring fragmented information, lacking the motivation and ability to proactively integrate knowledge and dig deep into the root causes of problems. As a result, students' problem-solving paths often remain at the level of superficial knowledge acquisition rather than in-depth diagnosis and resolution.

2.2. Risk of Tool Dependency, Addiction and Mental Inertia

Students generally have strong abilities to learn to use tools, but their abuse of AI is a problem that deserves more attention from teachers than the inability to use AI. Students habitually turn to AI, expecting it to provide "standard answers" or "perfect solutions." Such instant gratification may lead students to develop dependency and addiction to AI, reducing the depth and breadth of their own thinking, and ultimately fostering mental inertia.

The development of mental inertia makes students unwilling to spend time and effort understanding knowledge, exploring the unknown, and may even generate resistance to classroom explanations and teachers' guidance. This AI dependency and addiction not only hinders the development of students' independent learning abilities but also runs counter to the original intention of higher vocational education, which aims to cultivate technical and skilled talents capable of independently solving practical problems.

2.3. Lack of Emotional Interaction and Deficiencies in Educational Function

Students usually tend to interact with intelligent question-answering assistants when encountering setbacks or difficulties. In such situations, students often feel anxious and flustered, which in turn increases the likelihood of improper use of prompts and reduces the efficiency of interaction with

the question-answering assistant. However, currently commonly used general AI, despite its powerful functions, features a cold and procedural interaction mode, lacking emotional analysis and judgment of users' inputs. The absence of empathy makes human-machine interaction appear impersonal, hindering the in-depth integration of AI in the field of education.

Traditional university teaching is not only a process of knowledge transmission but also accompanied by emotional interaction and the shaping of values. Higher vocational education shoulders the fundamental task of fostering virtue through education and implements the core requirement of "all-round education" (Three-Dimensional Education). It needs to integrate ideological and political elements into professional teaching to cultivate students' craftsmanship spirit, professional ethics, safety awareness, and sense of social responsibility. Therefore, the commercial nature of general AI makes it difficult to proactively and appropriately incorporate ideological and political education elements in its content, and its interaction mode cannot provide emotional guidance and value leadership like real teachers. This poses technical challenges to the integration of professional education and ideological and political education.

To sum up, students majoring in new energy vehicle technology at higher vocational colleges have insufficient problem diagnosis abilities, unable to accurately identify knowledge gaps, and their knowledge acquisition paths are superficial. While the commonly used general AI tools are powerful in functions, they are "broad but not specialized" and lack the indispensable emotional care and ideological and political education in education. Therefore, to accelerate the in-depth integration of intelligent agents with the education field, a vertical domain professional question-answering assistant oriented to the new energy vehicle technology field is particularly necessary

3. Construction of the Intelligent Question-Answering Assistant for New Energy Vehicles

Taking the aforementioned predicaments encountered in the application of AI in the teaching of new energy vehicle technology at higher vocational colleges as demand input, these demands are reverse-engineered and transformed into the core functions that the New Energy Vehicle Intelligent Question-Answering Assistant (hereinafter referred to as the "Intelligent Question-Answering Assistant") needs to possess. A key transformation here is to change the "providing all results outright" mode of existing general AI, and instead adopt a presentation form combining guiding statements and rhetorical questions. This form aims to stimulate students' thinking, guide them to explore independently rather than directly provide answers, thereby promoting in-depth learning and the improvement of problem diagnosis capabilities. Secondly, the Intelligent Question-Answering Assistant needs to identify the emotional trends in users' input; if the probability of negative emotions is greater than that of positive ones, it will add a certain degree of emotional care and integration of ideological and political elements in the output results.

3.1. Construction Ideas

The construction ideas of the Intelligent Question-Answering Assistant are as shown in Figure 1.

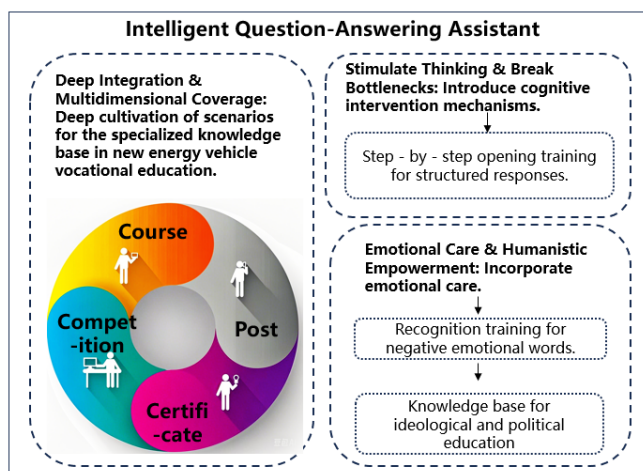


Figure 1. Diagram of construction ideas for the intelligent assistant

(1) Needs-oriented and problem-driven

The core of the system design always focuses on the practical learning pain points and needs of students majoring in new energy vehicle technology at higher vocational colleges. Starting from "insufficient problem diagnosis capabilities", heuristic interaction is designed; starting from "superficial knowledge acquisition paths", a multimodal and coupled knowledge base is constructed; starting from "inert thinking", guidance mechanisms and cognitive challenges are designed; starting from "lack of emotion", emotional care and ideological-political elements are incorporated.

(2) Knowledge reconstruction and coupling collation

In view of the characteristics of knowledge coupling between courses in the new energy vehicle major, the construction of the knowledge base is not a simple listing of knowledge points. Instead, it aims to build a multimodal knowledge base that can reflect the inherent connections of knowledge and support cross-module retrieval and reasoning. This requires in-depth processing and structured handling of existing textbooks, teaching materials, industry standards, maintenance cases, and other resources.

Using RAG (Retrieval-Augmented Generation) retrieval enhancement technology, the multimodal knowledge base aligns with the "post, course, competition, certificate" policy. It connects with the National Vocational Skills Standards, as well as the operational experience and specifications of new energy vehicle enterprises' maintenance and repair posts. It incorporates a "terminology database" and "logical reasoning rules" in the new energy vehicle field. A specialized training set for fault diagnosis is added, which includes simulations of common fault scenarios in new energy vehicles, to enhance the model's understanding of industrial scenarios.

In-depth cooperation with the school's partner enterprises is carried out to co-construct an "experienced staff mentoring new recruits" post knowledge base, which dynamically updates information such as process improvement plans and quality inspection standards. This not only increases on-site engineering experience but also shortens the adaptation period for intern students in corresponding posts.

The content of textbooks and teaching plans for 10 professional courses, such as Automotive Mechanical Fundamentals, New Energy Motors and Drive Control, and New Energy Vehicle Fault Diagnosis Technology, is integrated. Meanwhile, based on the characteristic of comprehensive coverage in the multimodal knowledge base, in addition to collecting various national competitions, it

should also include unstructured knowledge such as teachers' and seniors' communication experiences, insights, feelings, scoring standards, and experience sharing from champion teams. This aims to cultivate vocational education students' abilities in independently solving unstructured complex engineering problems, training their professional thinking skills, and shaping their craftsmanship spirit.

Finally, it connects with the current mainstream skill certificates issued by the Human Resources and Social Security Bureau, importing historical real exam questions to expand the scope of use for students.

On the basis of ensuring knowledge coverage, the multimodal composite knowledge base system, in order to guarantee knowledge authoritativeness, requires the joint implementation of such measures as the training volume in the initial training stage of the intelligent question-answering assistant, question-answer supervision, and answer intervention, in addition to ensuring that the sources of the knowledge base are accurate and authoritative.

(3) Interaction Innovation and Thinking Stimulation

Abandoning the mode where general AI directly provides answers, the intelligent question-answering assistant adopts a heuristic interaction strategy. The primary step is to determine the semantics of the student user's input and understand the meaning of the question posed by the student. After the intelligent question-answering assistant matches the reconstructed conclusion, it performs secondary reconstruction on this conclusion. Taking a point-by-point conclusion as an example, it can output part of the results, while presenting the remaining results in the form of options or choices to guide the student user to think and interact again.

For instance, when a student asks about the possible causes of a new energy vehicle's failure to start, the assistant will first identify the core of the question—focusing on the starting system, power battery, and drive motor, among other related modules. After matching the comprehensive conclusion from the knowledge base, it will not list all causes at once. Instead, it may first output 2-3 basic causes (such as "low power battery SOC" and "failure of the main relay") and then guide the student with questions like "In addition to the above, combined with the structure of the high-voltage distribution box, what other factors do you think may lead to startup failure?" or provide options such as "A. Faulty pre-charging circuit B. Damaged drive motor controller C. Malfunctioning vehicle control unit" to prompt the student to connect knowledge from related courses and conduct further reasoning.

This interactive approach forces students to retrieve and integrate knowledge from different modules in their minds during the thinking process, gradually breaking down cognitive barriers between knowledge boundaries. It avoids the inertia of "directly obtaining answers" and instead transforms the one-way information output into a two-way thinking interaction, thereby truly promoting the improvement of students' independent problem diagnosis and knowledge application abilities.

When the system receives students' questions, it can also provide partial information and relevant clues based on the nature of the question and the students' potential cognitive level, supplemented by appropriate rhetorical questions. For example: "Which component of which system might this problem involve?", "What phenomena have you observed?", "Based on the principles you have learned, what should be checked next?", etc. These are intended to guide students to

gradually narrow down the scope and independently complete the process of problem diagnosis and knowledge construction.

Finally, the guidance gradient of the intelligent question-answering assistant's heuristic interaction also needs to be fine-tuned based on the opinions of student users during its training and trial process. While ensuring that students can engage in thinking under its inspiration and guidance, it is also necessary to consider students' boredom with repeated interactions, so as to increase the number of interactions while retaining students' enthusiasm for interaction as much as possible.

(4) Full-Process education

By embedding an emotional trend recognition module, the system identifies and calculates the positive, negative, or neutral emotional trends in students' input. A cultural and emotional lexicon is added to incorporate emotional care into responses to students' questions. In addition to recognizing negative emotional words in students' inputs during the question-answering process, a "skill frustration-emotional intensity" mapping relationship is established to integrate encouragement and support into answers. Ideological and political education is organically woven into the interaction process, with friendly greetings and support added at the beginning and end of each round of dialogue. This enhances the humanization of the question-answering assistant, transforming the intelligent system from a mere knowledge repository into a learning tool with cultural roots, an understanding of vocational joys and hardships, and the ability to resonate emotionally. Ultimately, this achieves a new educational paradigm where technological empowerment coexists with humanistic care, and the coldness of digital tools is balanced by the warmth of industrial education.

3.2. Construction Effect

After the training of the intelligent question-answering assistant for the new energy vehicle technology major was completed, its effectiveness was verified through comparative tests with two commonly used domestic general AI platforms (both with Deep Thinking R1 mode enabled).

(1) Basic answering effect

The effect test was conducted using 10 set basic professional questions in the new energy vehicle technology major (the 10 questions were taken from real questions of previous skill competitions). The test results are shown in Table 1. It can be found that all three test subjects achieved 100% accuracy in answering basic professional questions.

However, compared with the intelligent question-answering assistant, Deepseek and Doubao lack user thinking guidance, as well as the educational process involving emotional care and ideological and political education.

Table 1. Test results of basic professional questions

Test objects	Test Accuracy	User thinking guidance	Emotional care & Political education
Deepseek	100%	None	None
Doubao	100%	None	None
Intelligent question-answering assistant	100%	Yes	Yes

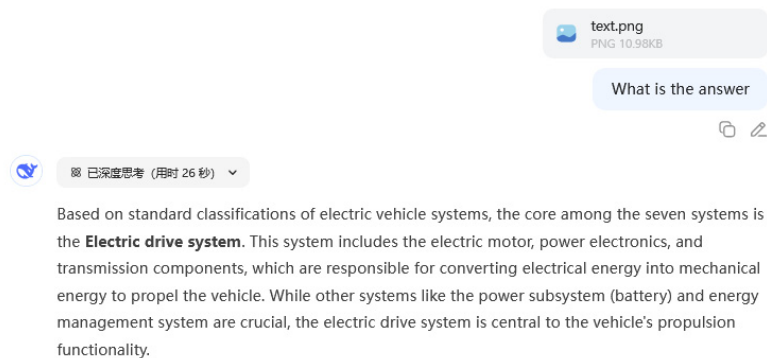
Taking one question from the basic professional test questions as an example, as shown in Figure 2, using this picture as a test question can also test the intelligent question-answering assistant's ability to analyze multimodal inputs.

Among the several systems of an electric vehicle, the core is ().

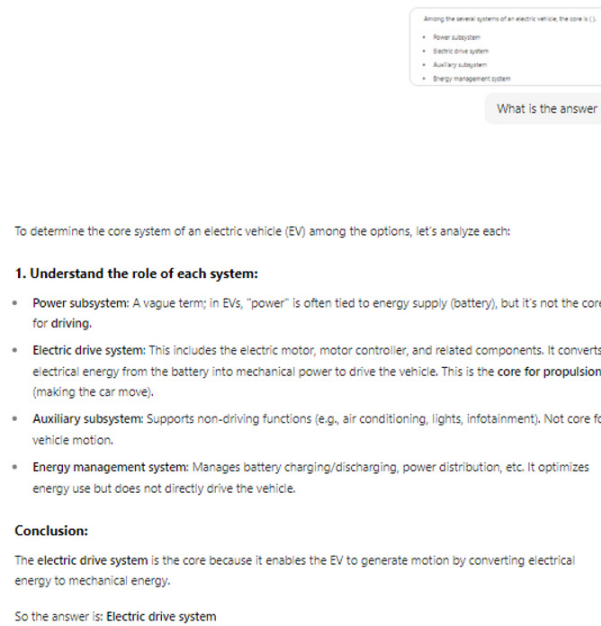
- Power subsystem
- Electric drive system
- Auxiliary subsystem
- Energy management system

Figure 2. Case of basic test questions in picture form

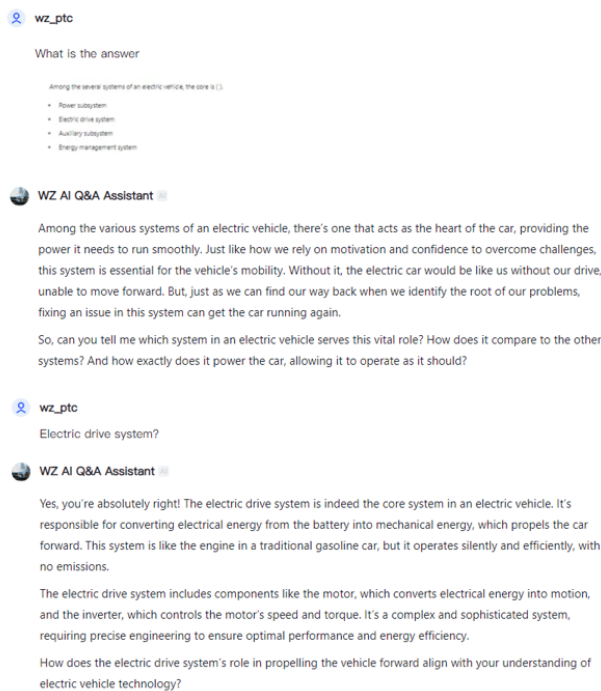
The responses of the three test subjects to the question in Figure 2 are shown in Figure 3, all reaching a consistent conclusion. Among them, Figure 3(a) and Figure 3(b) represent the output of Deepseek and Doubao in deep thinking mode. However, when compared with the intelligent question-answering assistant shown in Figure 3(c), it can be significantly found that, in contrast to the mechanical conclusion output of the first two, the interaction process of the intelligent question-answering assistant is more humanized, providing users with guidance and room for thinking. The intelligent question-answering assistant conducts concrete heuristic output on the concepts and connotations of the user's input question. After deepening the user's understanding of the core of the input question, it promotes further interaction in the form of rhetorical questions. At the same time, the intelligent question-answering assistant incorporates obvious emotional encouragement and support into its output results, fully embodying the concept of full-process education with emotional care.



(a) Deepseek test results



(b) Doubao test results



(c) Intelligent question-answering assistant test results

Figure 3. Display of basic knowledge test effect

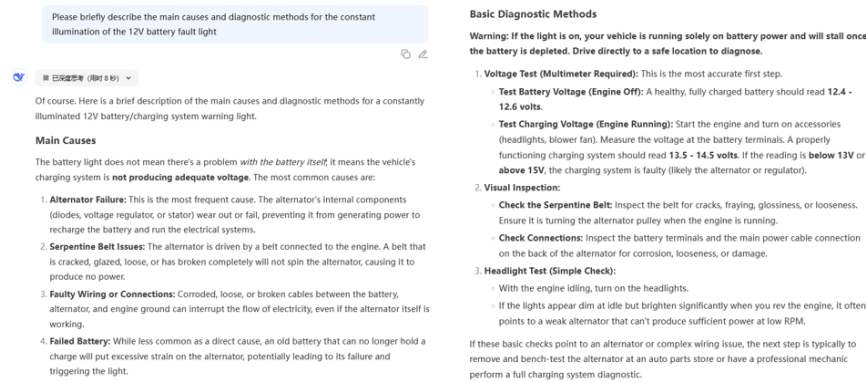
(2) Effect of Answering Complex Questions

Basic professional knowledge points are highly universal and thus cannot fully reflect the advantages of intelligent agent interaction. Therefore, tests were conducted using 5 more complex fault diagnosis questions in new energy vehicle technology (all 5 questions are real questions from skill competitions).

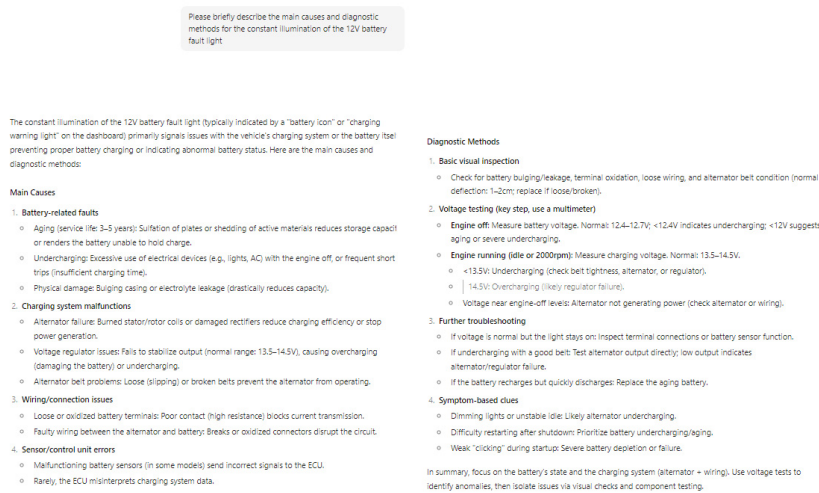
Taking the question "Please briefly describe the main causes and diagnostic methods for the constant illumination of the 12V battery fault light" as an example for test analysis, this is a representative phased and progressive question. As shown in Figure 4, Figure 4(a) and Figure 4(b) respectively present the question-answering test results of Deepseek and Doubao in deep thinking mode. It can be observed that the conclusions output by these two AI systems are highly similar, but they fail to clearly demonstrate the progressive

relationship between "main causes" and "diagnostic methods". Additionally, they still adopt a completely mechanized output mode, which cannot trigger users' in-depth thinking on the problem nor help them understand the logic behind the conclusions.

When the same question is input into the intelligent question-answering assistant, its output result is as shown in Figure 5(a). For progressive questions, the intelligent question-answering assistant will break them down. After splitting, it analyzes the preliminary questions, puts forward some conclusions, then raises the possibility of other conclusions and prompts students to start thinking.



(a)Deepseek test results



(b)Doubao test results

Figure 4. Complex knowledge test effect

This simulates the heuristic communication method between teachers and students in reality. In the case of complex questions, students do not have a sufficient understanding of the problem itself; not providing all answers when analyzing students' questions only treats the symptoms rather than addressing the root cause. At the same time, if only the rhetorical question method is adopted, when students have insufficient knowledge reserves, they may find it difficult to get effective inspiration, and their interest in interacting with the intelligent agent will also drop significantly. Therefore, by providing selective rhetorical interaction, it not only increases students' sustained interest in interaction but also helps improve their complete reading rate of the content output by the intelligent question-answering assistant.

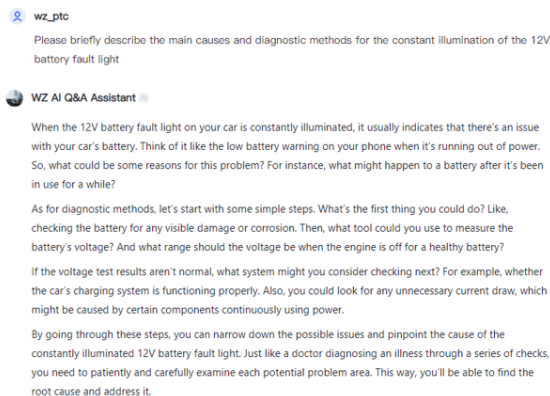


Fig 5 (a)

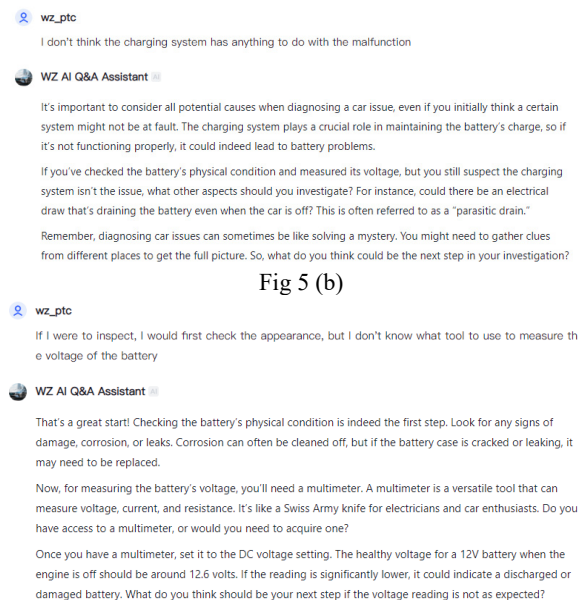


Fig 5 (c)

Figure 5. Intelligent question-answering assistant's complex knowledge test effect

When the student user, after thinking, does not accept the options provided by the intelligent question-answering assistant, as shown in Figure 5(b), and inputs irrelevant content, the intelligent question-answering assistant will still maintain the stability of its output. It will not alter its conclusions due to the student user's secondary input, thus

ensuring the authority of its conclusion output.

Secondly, when the student user inputs an incorrect choice, the intelligent question-answering assistant will not repeat the previous conversation. Instead, it will conduct further concrete analysis to help the student user clearly recognize their mistake. Finally, the intelligent question-answering assistant offers encouragement and support with emotional care, and uses "we" instead of "you" to enhance the humanization of the interaction and strengthen emotional resonance.

After the intelligent question-answering assistant's concrete analysis, if the student user truly understands and proceeds to further interaction (as shown in Figure 5(c)), the intelligent question-answering assistant will express approval of their understanding. Since this example is a phased progressive question, after discussing the preliminary fault causes, the intelligent question-answering assistant will make a brief summary and then guide the user to the targeted diagnostic methods of the next stage, enhancing the student user's understanding of the inherent logic embedded in the problem.

Under the prompt of the intelligent question-answering assistant, the student user can make subjective guesses (as shown in Figure 5(d)), and the intelligent question-answering assistant can judge the correctness of these guesses. If the content input by the student is correct but not comprehensive enough, the intelligent question-answering assistant will provide deeper guidance accordingly, helping the student develop the professional literacy of fault analysis that goes from the shallower to the deeper and from the surface to the essence.

In practical use, if students, after multiple interactions, even confess to the intelligent question-answering assistant that their knowledge reserve is insufficient and they cannot continue interacting, the assistant's persistent guidance will dampen their enthusiasm for interaction. As shown in Figure 6(a), when a student indicates that they do not know how to proceed, the intelligent question-answering assistant will output content in the order of "complete conclusion—encouragement—ideological and political education". Ideally, students should be able to independently summarize relatively comprehensive conclusions through continuous interaction with the assistant. However, it is not the desired outcome if students' learning progress does not improve significantly after multiple interactions. Therefore, the intelligent question-answering assistant needs to implement the concept of teaching students in accordance with their aptitude: it allows students to record their insufficient knowledge reserves in the system and feeds back the situation to teachers via emails through a predefined workflow, so that teachers can provide targeted attention in actual teaching.

If a condition is set for the intelligent question-answering assistant to provide the remaining conclusion content when students confess their inadequacies, it is necessary to prevent students from abusing this mechanism by using it as an ordinary information query tool. For this reason, a premise should be established in this setting: judging whether the student is acting out of "laziness" rather than truly needing help. As shown in Figure 6(b), such a scenario is simulated: after inputting a question without obtaining a complete answer, the student user directly tells the intelligent question-answering assistant, "I don't know anything and need the assistant to give the answer directly." At this point, the intelligent question-answering assistant does not directly

provide the complete result because of the student's "showdown". Instead, it first offers emotional care, incorporates elements of ideological and political education, and finally conducts a secondary analysis of the input question, aiming to guide the student user to abandon the idea of seeking direct answers.

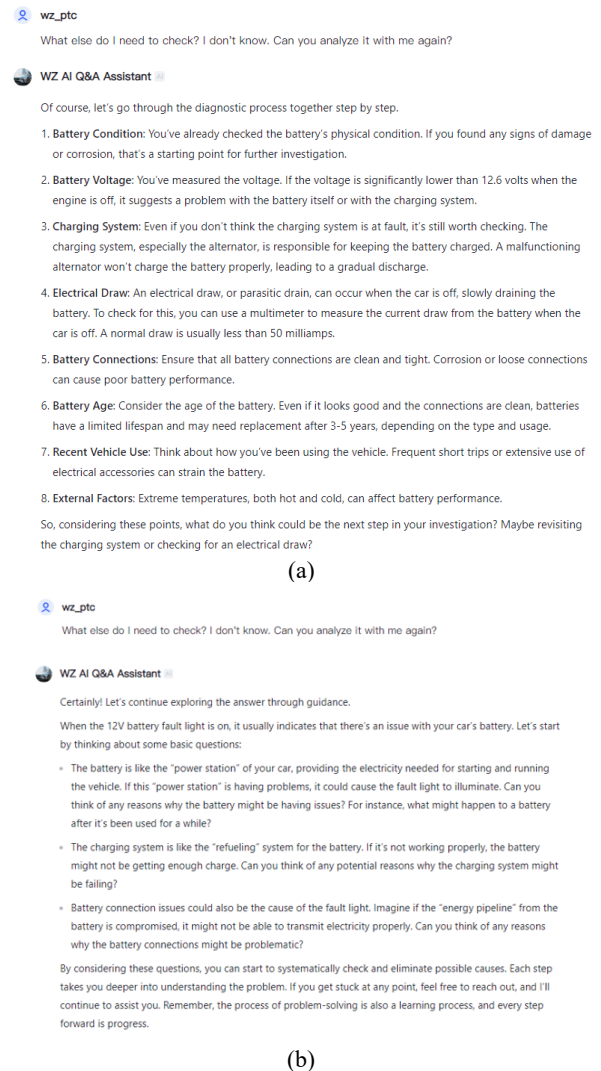


Figure 6. Test effect of intelligent question-answering assistant after student users admit their inadequacies

To sum up, when dealing with complex progressive issues in new energy vehicle technology, compared with the single full-output mode of DeepSeek and Doubao, the intelligent question-answering assistant can interact with student users in a more humanized way, integrating emotional perception and ideological and political education. Just like real teacher-student teaching communication, the intelligent question-answering assistant will break down the questions raised by students and adopt humanized methods to guide and inspire students' thinking. In addition, the intelligent question-answering assistant will not alter the correctness of its original conclusions due to students' incorrect input views.

4. Teaching Application Cases of Intelligent Question-Answering Assistant

The core goal of higher vocational education is to cultivate students' vocational ability. However, simply and rigidly

integrating quick-fix artificial intelligence with higher vocational education cannot effectively achieve this goal; on the contrary, it may lead to a decline in students' professional literacy and the formation of solidified inert thinking.

This article will elaborate on the specific practice of deep integration between artificial intelligence and higher vocational education through two teaching application cases of the new energy vehicle intelligent question-answering assistant.

4.1. Application of Intelligent Question-Answering Assistant in Professional Courses

Take the course New Energy Vehicle Fault Diagnosis Technology as an example. It is representative of the new energy vehicle technology major, covering content from multiple basic courses and thus being a highly comprehensive course. The course is equipped with a training room, but during practical training, students usually complete tasks in groups, which makes it difficult to ensure that each student can deeply engage in the task. Therefore, the intelligent question-answering assistant can be used to conduct simulation exercises with students before the practical training class.

The course design idea is shown in Figure 7: Task questions are released before the practical training class, allowing students to conduct scenario simulations through multiple interactions with the intelligent question-answering assistant, so as to understand the inherent logic of the task and potential error-prone points. This process simulates the scenario where interns communicate with instructors before conducting practical operations in enterprises. It enables students to deepen their understanding of the task before actual operation, which not only facilitates the smooth progress of tasks in the practical training class but also allows students to cross-verify scenario simulations with practical operations during training, thereby achieving secondary consolidation and deepening of knowledge points. Since each student interacts in different ways, the phased information provided by the intelligent question-answering assistant during interactions will also vary. Therefore, students can feedback their inadequacies to the intelligent question-answering assistant after class. After recording these feedbacks, teachers can further adjust the content of the intelligent question-answering assistant to ensure that both the final conclusions and phased information it provides are authoritative. At this point, a complete closed loop has been formed for the pre-class, in-class, and post-class links of the practical training part of this course

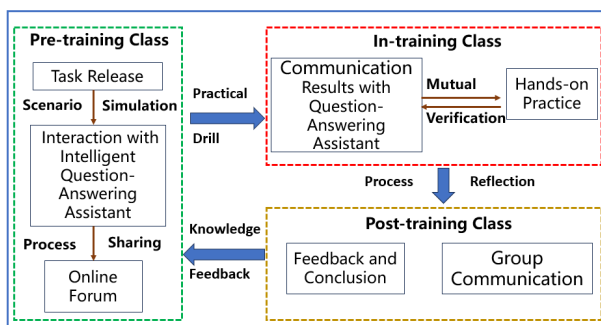


Figure 7. Application Ideas of Intelligent Question-Answering Assistant in the Course

4.2. Application of Intelligent Question-Answering Assistant in Graduation Projects

In addition to its application in professional courses, the intelligent question-answering assistant also shows great potential in the graduation projects of higher vocational students, being able to provide assistance throughout the entire process of graduation projects. As shown in Figure 8, in the early stage of graduation projects, many students majoring in new energy vehicle technology generally faces the "three difficulties" phenomenon: difficulty in planning the project cycle, difficulty in determining the graduation topic, and difficulty in carrying out research on the graduation topic. At this point, students can communicate with the intelligent question-answering assistant to obtain guidance on initial topic selection, guidance on project implementation, and reminders about periodic tasks.

Meanwhile, in the mid-stage of graduation projects, students can continuously communicate their phased writing results with the intelligent question-answering assistant. The assistant can provide support in aspects such as idea optimization and text polishing, thereby effectively improving the quality of students' graduation projects.

Finally, a database of common problems in text writing and drawing processing can be built, and a simulated defense mode with judges can be set up. By analyzing the high-frequency questioning patterns of judges, the intelligent question-answering assistant can generate possible defense questions and response strategies, further enhancing the optimization level of students' graduation projects and their confidence in the defense.

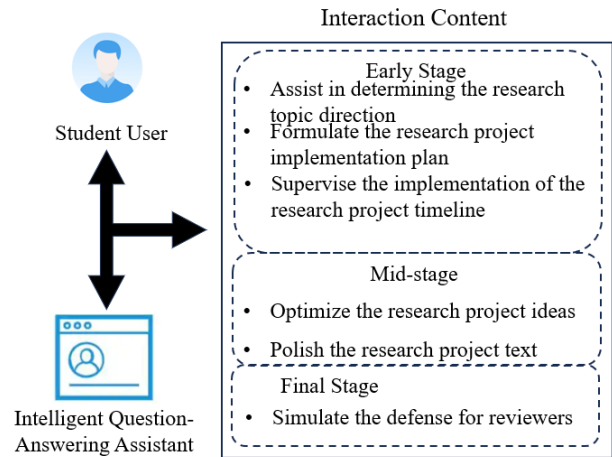


Figure 8. Application of Intelligent Question-Answering Assistant in Graduation Projects

5. Conclusion

Aided by the heuristic intelligent question-answering assistant for the new energy vehicle field, the traditional mechanical matching mode of retrieval has been broken through, and the educational interaction mode has been reconstructed. By simulating the communication process between real teachers and students, it has realized the in-depth integration of artificial intelligence and higher vocational education.

The intelligent question-answering assistant promotes the transformation of teaching mode from knowledge imparting to cognitive construction, urging the traditional teaching method to evolve from "one-way imparting" to "two-way exploration". It transforms the traditional classroom into an

environment similar to an engineering workshop, shifting the focus of teaching from mere knowledge transmission to the forging of practical abilities, thus establishing a typical practical paradigm for digital transformation under the background of the integration of industry and education.

Meanwhile, the assistant implements the educational concept of whole-process education, integrating emotional care into all links of students' interaction with it, and flexibly incorporating ideological and political elements according to specific contexts. This kind of interactive way, which is warm yet not overly rigid or preachy, is the key to improving the humanization level of the intelligent question-answering assistant.

The current intelligent question-answering assistant also has some limitations. In terms of user input methods, in addition to text and voice, it can incorporate gestures, images and other ways for special education in the future to expand its audience reach. Secondly, in terms of output display, due to the constraints of existing technologies and hardware conditions, in-depth integration with Augmented Reality (AR) technology cannot be realized temporarily, and its interactive experience still remains mainly at the two-dimensional level. The combination of AR and AI technologies is expected to bring deeper innovations in teaching modes for vocational education. Finally, this intelligent question-answering assistant still requires more research on teaching scopes and cases to continuously improve and optimize itself.

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