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Evaluation model of new energy vehicle teaching effect based on artificial intelligence

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ABSTRACT

As a compulsory course, the new energy vehicle course should be reformed in regard to the teaching methods and content. This paper summarises the characteristics of this course based on the author's practice. This project studies the new energy vehicle teaching cloud evaluation method based on a big data environment. The reverse cloud generator and cloud synthesis algorithm are used to build a new energy vehicle teaching evaluation system. Secondly, based on determining the weight cloud of the teaching evaluation index and task weight cloud, the cloud computing rules are used to generate the single-task teaching evaluation cloud and the multi-task complex teaching evaluation cloud, respectively. The complex teaching choices are evaluated and optimised. An example shows that the proposed algorithm is practical and reasonable. This paper's research results will help evaluate the quality of education more comprehensively and promote the smooth progress of education reform.

KEYWORDS Big data; cloud computing; new energy vehicles; reverse cloud generator; educational assessment; educational reform
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1. Introduction

The rapid development of China's new energy vehicle industry and the urgent need for specialised technicians in the field of new energy vehicles will certainly promote teaching reform in the field of new energy vehicles in China. New energy vehicles are the future development trend. Since 2009, China has been the world's second-largest consumer market for new energy vehicles. The development of new energy vehicles has played a significant role in China's economic development and has also driven people's daily consumption, which requires the teaching of new energy vehicles to keep up with the pace of the times to cultivate a new generation of talents. This will promote the sustainable and rapid development of new energy vehicles. However, from the teaching method and teaching content, the teaching related to new energy vehicles needs to be improved.

There are scholars who have analysed the relevant teaching mode according to its practice in the introduction course of new energy vehicles (Abbasi et al., 2021). There are scholars who believe that cooperation between enterprises and schools can strengthen the training of relevant skills for students, thus providing a new way to cultivate automotive new energy technical talents in higher vocational schools (Inderwildi et al., 2020). There are scholars who have discussed the thematic research on new energy vehicles (How et al., 2020). However, most existing studies have summarised the teaching mode of new energy vehicles according to their practice, and there is a lack of quantitative application research (Husin and Zaki, 2021). Therefore, this project was intended to study a complex educational cloud evaluation method based on big data. First, a composite education evaluation model of new energy vehicles was constructed to obtain the primary evaluation data of teachers in the big data of new energy vehicle education (Zhao et al., 2023). The corresponding evaluation cloud was generated using the reverse cloud generator. Secondly, cloud computing technology was used to generate an evaluation system to generate a teaching evaluation index. Then, according to the weighted coefficient of each evaluation index and the operation rule of cloud computing, the teaching evaluation cloud system of a single assignment was obtained (Murshed, 2020). The multi-task composite teaching evaluation system was constructed by using cloud computing rules. The multi-task composite teaching evaluation system of new energy vehicles was constructed by integrating it with the job-weighted and single-job teaching evaluation cloud. In this way, the evaluation and optimisation of multi-task composite teaching schemes were realised (Chen et al., 2022).

2. Knowledge sharing process in the field of new energy vehicle education

2.1. Knowledge sharing in industrial education

In the knowledge sharing in industrial education, teachers integrate new knowledge resources into their existing knowledge. Through knowledge learning, new knowledge can be formed to enhance the core competence of an enterprise (Abbasi et al., 2020). This new knowledge is shared with other participants through educational knowledge networks to improve the knowledge throughout

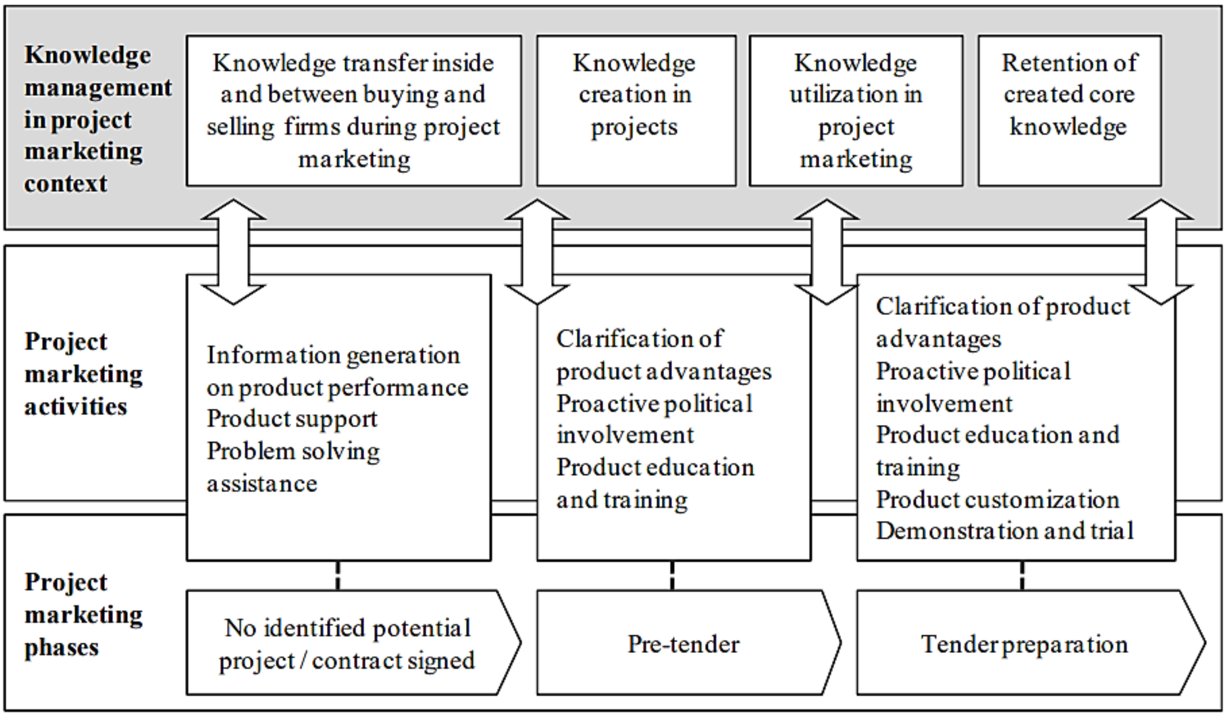

Figure 1. Knowledge sharing process of industrial teaching.

education. Educational enterprises are constantly transferring part of the new knowledge to the network through the acquisition and innovation of the innovative knowledge propagated in the storage network. Knowledge is acquired, stored, served, and shared (Figure 1) (Basit et al., 2020).

2.1.1. Knowledge acquisition process

Industrial education is a collective process. The most critical performance in acquiring knowledge of industrial education is the teacher's mastery and integration of knowledge resources through knowledge acquisition (He et al., 2020). The most important thing for industrial education is to selectively acquire knowledge according to needs and internalise it to expand the internal knowledge resources.

2.1.2. Knowledge storage process

In industrial education, teachers must maintain the sustainable development of industrial education through continuous scientific and technological innovation (Ahmadian et al., 2020). Through the standardised storage and classification of knowledge obtained in various ways, teachers can grasp the development course of the subject. More valuable information can be obtained through the in-depth analysis of the stored knowledge to promote knowledge innovation in industrial education.

2.1.3. Knowledge service process

Industrial education uses the power of teachers to provide specific knowledge resources. After teachers have obtained the knowledge resources that they need, they give feedback on the information of knowledge service according to their creative ability and sharing intention (Li et al., 2020). According to the feedback, teachers redistribute and authorise re-planning to adjust the knowledge resources teachers' store. This promotes high-level knowledge sharing among more teachers.

2.2. Acquisition of industrial teaching knowledge

The acquisition of teaching knowledge in industrial teaching can be divided into external teaching, teaching member enterprises, and teaching member enterprises. Knowledge acquisition is an integral part of knowledge sharing. According to the core competitiveness strategy and knowledge-sharing ability of teaching member enterprises, enterprises with relatively weak knowledge resources and little contribution to teaching knowledge sharing will be selected purposefully. In this way, the dynamic and rapid capture of knowledge resources outside teaching is realised, which plays a vital role in the core competitiveness of enterprises (Adaikkappan and Sathiyamoorthy, 2022).

(1) Under the influence of market competition, there is an "atmosphere of trust" inside the enterprise, which makes the enterprise worry about the spillover of

core knowledge and then triggers the spillover of knowledge inside the enterprise. This will reduce the enterprise's voice in the field. The enterprise has adopted high confidentiality measures for technology, experience, management methods, and methods. The paper should strengthen the mutual trust between the teaching parties and reduce the pressure of knowledge protection. It also provides more guarantees for collaborative development in competitive situations (Cooper, 2023).

(2) Tacit knowledge is hidden and difficult to learn. This increases the difficulty of sharing and learning between teachers. If the requirements for its "concealment" are higher, then its "carrier" maintenance is also more significant. Therefore, teachers must provide specific knowledge acquisition rules to encourage teachers to share tacit knowledge actively. In this way, teachers can obtain the necessary tacit knowledge to improve the enterprise's mastery of tacit knowledge. When there is a definite knowledge exchange between member enterprises in industrial education, enterprises with cooperation or competition must put forward a specific process mode from the perspective of knowledge sharing. It is necessary to strengthen the sharing of human resources to enhance the enthusiasm for knowledge sharing among organisations.

(3) The knowledge stock, learning ability, and absorption capacity of teachers in the industry are different, and the correlation of teachers' knowledge leads to the difference in knowledge position among teachers' enterprises. The greater the knowledge difference, the more likely they are to have knowledge-sharing deficiencies in knowledge acquisition and sharing. At the same time, their value to the supply and demand of knowledge resources will also increase (Godil et al., 2021). This leads to different views on knowledge sharing and acquisition among teachers. When the connection between enterprises and education becomes increasingly close, enterprises must occupy a better position in the education process to obtain more valuable knowledge. This advantage depends on the enterprise's "knowledge learning" and the degree to which teachers and students know each other. If the research team does not establish a high level of early trust, then the teaching member partners are replaced by other teaching members in the process of cooperation or competition, and it is easy to be replaced by the partner. Then, it is necessary to find the enterprises that can provide them with more knowledge resources to enhance the complementarity of the knowledge resources among enterprises.

2.3. Industrial teaching knowledge storage

Industrial teaching knowledge storage is an essential link in industrial education knowledge processing. Its purpose is to enable teachers to obtain educational knowledge from all kinds of resources and realise the innovation and sharing of educational knowledge. In the process of knowledge storage, industrial education is guided by the knowledge-sharing platform of the core curriculum. Through a series of ways to obtain the external knowledge needed for education, it provides a bold hypothesis or method for creating and sharing knowledge.

At present, a knowledge warehouse has been widely used in the knowledge warehouses of enterprises. As an extension of a data warehouse, it has the advantages of massive data, rich historical data, fast querying, and so on. In industrial education knowledge sharing, the knowledge warehouse constitutes the core component of the industrial education cloud platform, which ensures the safety of education resources and also becomes the primary way for teachers to obtain knowledge services. This requires a higher demand for information technology. It includes high-performance, reliable development, and processing technologies. At the same time, the reasonable allocation of hardware resources, the pre-processing and fast collection of knowledge, the application of information technology, and the guarantee of knowledge are also related requirements. According to the different kinds of knowledge resources, corresponding methods should be adopted accordingly. Codable knowledge is dynamically encoded, while non-coded implicit knowledge must be learned by collaborative members among teachers and stored on the learner's application platform. It is centrally managed by knowledge managers to prevent its leakage (Hosseini et al., 2020).

The knowledge warehouse in the industrial teaching cloud platform is based on the network. It is a mixed type of knowledge resource. The hybrid knowledge resource database, which combines relational and knowledge warehouses, can effectively improve the industry's storage efficiency of knowledge resources. It can help teachers register quickly and realise information sharing and the acquisition of knowledge resources to ensure the safety of the knowledge resources. At the same time, it can promote the rapid acquisition of knowledge resources. Every professorial member has a server (Wei et al., 2020). The registrant stores three categories related to registration information: one is to store other teacher membership registration information queried by the member, as well as the subject number of the corresponding data and the website of its server. The second type is to record the login information of other members to which the member belongs, and save the member's code name and server address information. The third type refers to user account registration information, user information, user contact information, knowledge resource subject information, etc. (Ghasemy et al., 2020).

2.4. Industrial teaching knowledge service

The service of industrial education knowledge refers to the information exchange between teachers and the outside world. Teachers often transfer information as knowledge service providers and receivers in this process. In contrast, the receivers are disintegrators who "decompose" the acquired knowledge and integrate it into their knowledge resources to realise the transformation and innovation of the acquired knowledge. In this way, the efficiency of knowledge sharing of member enterprises is enhanced. The knowledge service in industrial education is affected by many factors, which makes it challenging to carry out effective knowledge transfer and service. Therefore, this project intended to study the knowledge service barriers in industrial education.

2.4.1. Teaching members' knowledge service attitude

Teachers are the main body of educational knowledge services in industry. Teachers' knowledge service must be carried out around the core knowledge resources to improve teachers' knowledge innovation ability. According to the economic value theory, teachers often strictly protect enterprises' core knowledge through information closure and knowledge distortion, and many collaborative projects among teachers will also take illegal ways to obtain the core knowledge of other core members (Shahzad, 2020). At the same time, there are considerable differences in the knowledge acquired by enterprises through participating in projects, which leads to the inefficiency of knowledge service and the inability to share educational knowledge.

2.4.2. Knowledge features

Knowledge features include two types of knowledge: explicit knowledge and implicit knowledge. Explicit knowledge can be attached to a specific knowledge carrier and manipulated by computer code, which helps to make various roles in the education system provide services to each other. Teachers can download, use and disseminate the explicit knowledge that they need according to their access rights (Wolske et al., 2020). Tacit knowledge mainly refers to the experiences and skills stored in the brain, which are difficult to store in a specific carrier or be expressed visually. Therefore, the diffusion of such knowledge is easily influenced by the service concept and attitude of the disseminators. Tacit knowledge holders can often use their tacit knowledge flexibly, so achieving a wide range of diffusion is not easy. In the knowledge service in the field of industrial education, if the proportion of tacit knowledge is too high, it will affect the knowledge service in the field of education.

2.4.3. The knowledge and skills gap between teachers

"Knowledge learning" is a kind of ability whereby teachers use various ways to convert and absorb the corresponding information resources after obtaining them. Because each teacher's enterprise has the same knowledge reserve, there are differences in learning among members with different research abilities. This will directly impact teachers' knowledge utilisation (Chien et al., 2022). In industrial education, if teachers' knowledge is not high before collaboration, it is easy to cause the knowledge service level within education to be low. The relationship between teachers and students has a differentiated effect on the knowledge which teachers provide. For example, the insufficient connection between teachers will directly affect the auxiliary information which teachers provide. This makes it difficult for teachers and students to obtain the corresponding information, thus reducing the efficiency of knowledge sharing among teachers. Due to the low level of mutual trust among institutions and the reluctance of teachers to share information, there will be some deficiencies in the process of knowledge service, which will reduce teachers' enthusiasm to invest in knowledge, which will hurt the quality of knowledge service.

3. New energy vehicle teaching evaluation model oriented to big data

If each enterprise in new energy vehicle education is regarded as a single subject, then the multi-agent of the new energy vehicle education system can be described as:

(1) $C = \{c_1, c_2, \cdots, c_i, \cdots, c_n\}$ to express the collection of teaching members. $\forall c_i \in C$ has a capacity source vector $D^i = [d_1^i, d_2^i, \cdots, d_j^i, \cdots, d_s^i]$ in dimension s. It reflects the capacity required by c_i to complete a specific task, and $d_j^i \geq 0$ is the Class j resource that c_i has. The s stands for the class of powers (Khurana et al., 2020).

(2) The work set stipulates that multiple jobs $U = \{u_1, u_2, \cdots, u_k, \cdots, u_m\}$ must be performed simultaneously, where job u_k represents job k. $\forall u_k \in U$ is a vector $L^{u_k} = [l_1^{u_k}, l_2^{u_k}, \cdots, l_j^{u_k}, \cdots, l_s^{u_k}]$ that requires a certain number of resources. $l_j^{u_k} \geq 0$ is the class j resource required for operation u_k.

(3) The real resource contribution degree in $\forall c_i \in C, \forall u_k \in U$ has an actual resource contribution degree vector. $E^{ki} = [e_1^{ki}, e_2^{ki}, \cdots, e_j^{ki}, \cdots, e_s^{ki}], 0 \leq e_j^{ki} \leq d_j^i$ represents the contribution by c_i to group u_k. If c_i is added to $u_k, e_j^{ki} > 0$, otherwise $e_j^{ki} = 0$.

(4) Teaching Z_{u_k} is associated with u_k single assignment A, and $Z_{u_k} \subseteq C, Z_{u_k} \neq \varnothing$ exists. There is a capability resource vector $D^{Z_{u_k}} = [d_1^{Z_{u_k}}, d_2^{Z_{u_k}}, \cdots, d_j^{Z_{u_k}}, \cdots, d_s^{Z_{u_k}}]$. $d_j^{Z_{u_k}} \geq 0$ represents the resource of type j owned by Z_{u_k}, so Z_{u_k}

accepts the resource limit of job u_k in the case of a single job.

$$d_j^{Z_{u_k}} \geq l_j^{u_k} (1 \leq j \leq s) . \tag{1}$$

(5) Multi-task teaching $Z = \{Z_{u_1}, Z_{u_2}, \cdots, Z_{u_k}, \cdots, Z_{u_m}\}$ is formed by undertaking multi-task U. Where C is the single-task teaching formed to undertake the task u_k, $Z \subseteq C, Z \neq \varnothing$. There is a capability resource vector $D^Z = [d_1^Z, d_2^Z, \cdots, d_j^Z, \cdots, d_s^Z]$, where $d_j^Z \geq 0$ represents the possession of the j kind of resource by teaching Z, and the resource constraint condition for multi-task teaching H to undertake multi-task U is

$$d_j^Z \geq \sum_{u_k \in U} l_j^{u_k} (1 \leq j \leq s, 1 \leq k \leq m) . \tag{2}$$

(6) Provide the income value of the professor's education income Z_k through a characteristic function $U(Z_k) \geq 0$:

$$U(Z_k) = Q(u_k) - G(Z_k) , \tag{3}$$

$Q(u_k)$ benefits from performing u_k work. $G(Z_k) = \sum_{c_i \in Z_k} \sum_j e_j^{ki}$ refers to the converted cost of all the human capital that teachers invest, including research and development expenses, manufacturing expenses, and other expenses. The overall benefits of several activities Z are as follows:

$$U(Z) = \sum_{k=1}^{m} U(Z_k) = \sum_{k=1}^{m} (Q(u_k) - G(Z_k)) , \tag{4}$$

The essence of complex teaching of new energy vehicles is to solve the corresponding education $Z = \{Z_{u_1}, Z_{u_2}, \cdots, Z_{u_k}, \cdots, Z_{u_m}\}$ through multiple tasks $U = \{u_1, u_2, \cdots, u_k, \cdots, u_m\}$ under certain resource constraints to maximise the overall benefit U_{MAS}.

$$U_{MAS} = \sum_{k=1}^{m} U(Z_k) . \tag{5}$$

4. Compound learning assessment model in the big data environment

4.1. Complex education system structure in the big data environment of new energy vehicles

With enterprises in the new energy vehicle education field as independent network nodes, a robust and comprehensive education network system was built around the big data processing and analysis platform (Wu et al., 2020). The big data processing and analysis platform is the medium to connect various enterprises. It can provide various services such as data collection, data processing, data analysis, data updating, and software calculation for all enterprises in the field of new energy vehicle education so that they can exchange data, integrate resources, and share information. A comprehensive, extensive data training framework based on new energy vehicles was constructed (Figure 2).

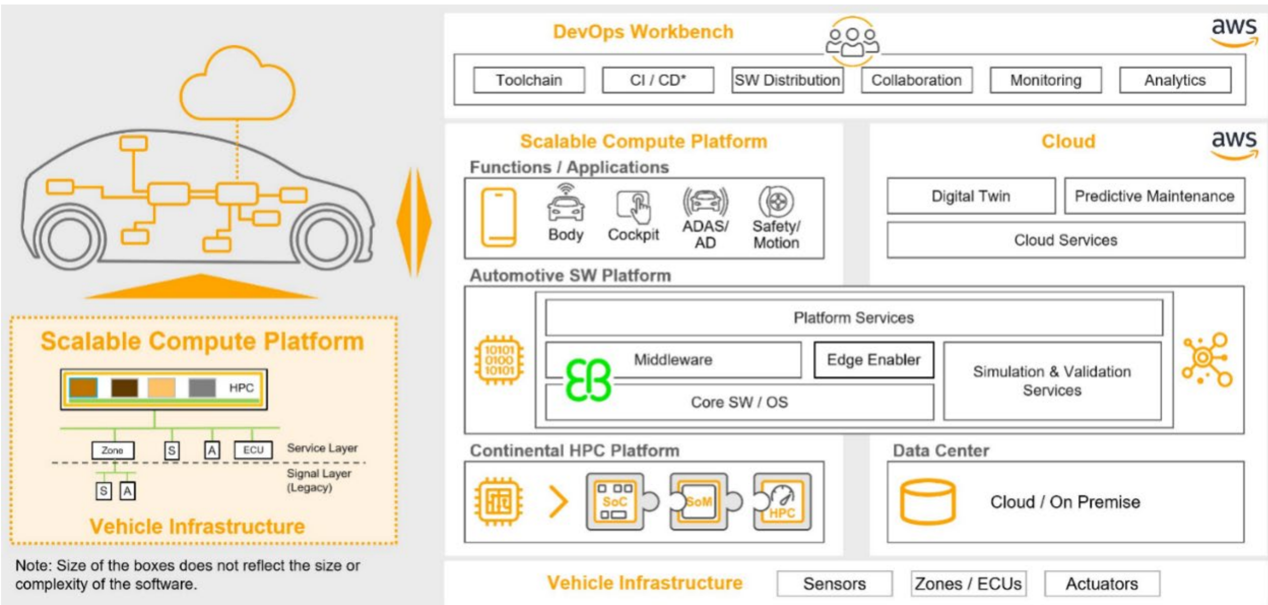

Figure 2. Complex teaching architecture of new energy vehicles for big data.

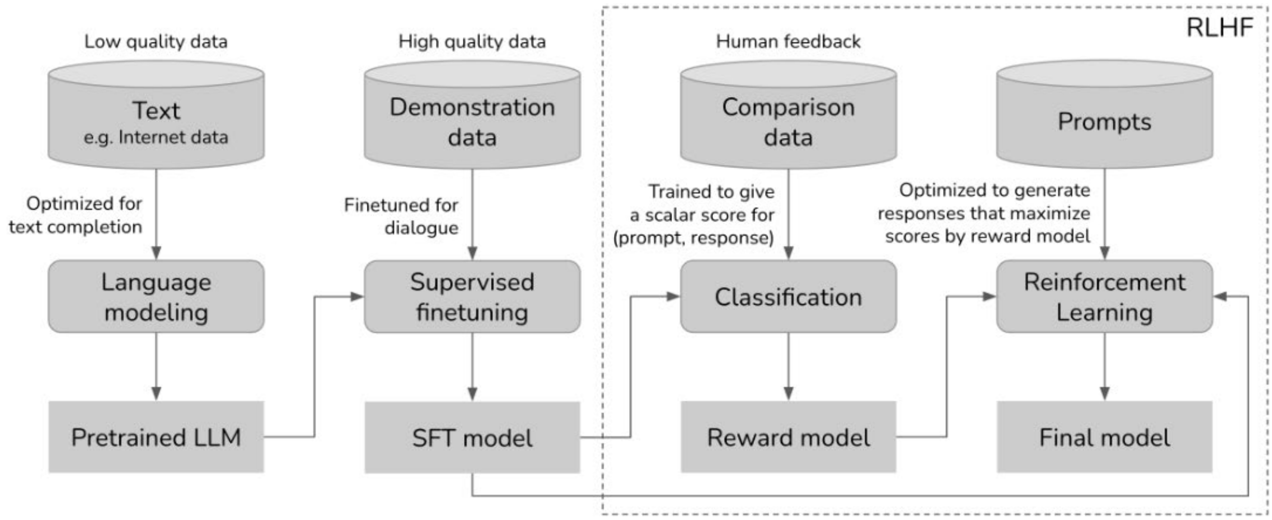

Figure 3. A complex teaching evaluation model for big data.

4.2. Complex teaching evaluation model for big data

There are n and $C=\{c_1,c_2,\cdots,c_i,\cdots,c_n\}$ enterprises. To undertake the task $U=\{u_1,u_2,\cdots,u_k,\cdots,u_m\}$, multi-task complex teaching for new energy vehicles $Z=\{Z_{u_1},Z_{u_2},\cdots,Z_{u_k},\cdots,Z_{u_m}\}$ is formed under the condition of meeting the resource constraints. Suppose that $U(Z_{u_k})$ represents the educational benefit Z_{u_k} from completing a single assignment u_k. $U(Z)$ represents the overall benefit of complex education Z resulting from multiple assignments. According to the teaching characteristics of the new energy vehicle industry, teaching is divided into three levels: essential index evaluation, single-task evaluation, and multi-task composite evaluation. The comprehensive evaluation $U(Z)$ is taken as the comprehensive evaluation index. Z_{u_k} is taken as the sub-target of single-task teaching evaluation, and the main factors affecting teaching income evaluation are taken as the primary index (Ali et al., 2021). A big data-oriented new energy vehicle complex teaching evaluation model is established (Figure 3). $Y_1,Y_2,\cdots,Y_h$ represents the influence of each factor on the effect of a single job, where h is the number of evaluation indices.

(1) The primary index data of each enterprise were collected using the random sampling method, and the reverse cloud generator constructed the evaluation cloud system. (2) The teaching index evaluation system of new energy vehicles was generated through cloud computing synthesis. (3) A single task-based learning assessment cloud and a multiple task-based compound learning assessment system were built to achieve comprehensive evaluation and optimisation of the new energy vehicle course learning options. A comprehensive study of the multiple factors in the evaluation of multi-task composite teaching for new energy vehicles was conducted. The main measurement criteria were teachers' teaching ability matching, student trust, teaching cost, and sustainability of educational investment. "Teachers' teaching ability matching" refers to the "matching degree" between a specific "skill" completed by a teacher and the "required ability", which can be measured by the Euclidean "distance". Student trust is a combination of direct trust and indirect trust values, and is determined by both direct trust and indirect trust values. Teaching cost is the sum of exchange costs between individuals in the education process. Educational investment sustainability means that teachers can still carry out the next step of work after completing their current job requirements.

4.3. Complex teaching evaluation of new energy vehicles based on cloud theory

A comprehensive evaluation system was established for teaching about new energy vehicles. An evaluation grading criteria cloud and evaluation cloud were constructed. An evaluation index system cloud, task weight cloud, single-task teaching evaluation cloud, and multi-task teaching evaluation cloud were constructed, and the generated new energy vehicle teaching evaluation cloud was evaluated and optimised (Figure 4 is quoted in Techno-economic Analysis and Life-Cycle Analysis of Renewable Diesel Fuels Produced with Waste Feedstocks).

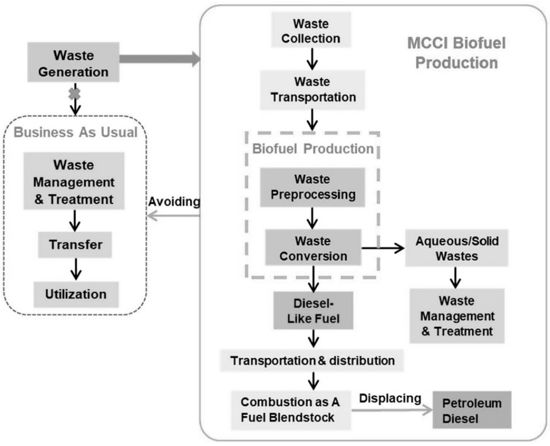

Figure 4. The complex teaching evaluation process of new energy vehicles based on cloud model theory.

4.4. Establishment of an evaluation set of evaluation indicators

The implementation effect of the new energy vehicle course was analysed. An evaluation index set $Y=\{Y_1,Y_2,\cdots,Y_h\}$ was constructed (Khurana et al., 2020).

4.5. Evaluation of the construction of hierarchical and standardised cloud computing models

This project obtained the interdomain values of each evaluation index and the corresponding cloud characteristic parameters through the inversion of cloud generation technology based on the big data of new energy vehicle education.

Table 1. Definition domain interval and cloud characteristic parameters of evaluation classification criteria.

Evaluation level	Domain interval	Cloud characteristic parameter
good	[0.80, 1.00]	(0.933, 0.038, 0.003)
preferably	[0.60, 0.80]	(0.701, 0.033, 0.001)
intermediate	[0.40, 0.60]	(0.596, 0.039, 0.003)
range	[0.20, 0.40]	(0.313, 0.031, 0.005)
poor	[0, 0.20]	(0.131, 0.035, 0.005)

4.6. Determination of the evaluation cloud of the teaching evaluation index

A random sampling method was adopted to obtain teachers' primary index evaluation data in various disciplines based on the big data of new energy vehicle education. The corresponding evaluation index cloud was constructed using a reverse cloud generator and other methods. Then, the cloud characteristic parameters used to evaluate the teaching evaluation index were generated through the cloud synthesis operation.

$$K^Z=\begin{bmatrix} K_1^{Z_{u_1}} & K_2^{Z_{u_1}} & \cdots & K_i^{Z_{u_1}} & \cdots & K_h^{Z_{u_1}} \\ K_1^{Z_{u_2}} & K_2^{Z_{u_2}} & \cdots & K_i^{Z_{u_2}} & \cdots & K_h^{Z_{u_2}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ K_1^{Z_{u_k}} & K_2^{Z_{u_k}} & \cdots & K_i^{Z_{u_k}} & \cdots & K_h^{Z_{u_k}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ K_1^{Z_{u_m}} & K_2^{Z_{u_m}} & \cdots & K_i^{Z_{u_m}} & \cdots & K_h^{Z_{u_m}} \end{bmatrix}, \tag{6}$$

$K_i^{Z_{u_k}}$ is the cloud characteristic parameter of the teaching evaluation index of item i of single exercise training Z_{u_k} in course Z.

4.7. Determination of the weight cloud of teaching evaluation indicators

According to the analysis of the importance of the teaching evaluation index $Y_1,Y_2,\cdots,Y_h$ to the teaching income evaluation, the weighted cloud $Y_1,Y_2,\cdots,Y_h$ of the evaluation index was set as $\mu=\{\mu_1,\mu_2,\cdots,\mu_i,\cdots,\mu_h\}$. μ_i is the weighted cloud $(Kx_{\mu_i},Kn_{\mu_i},Pe_{\mu_i})$ of the Teaching Assessment Index Y_i. The importance of the teaching evaluation index was divided into five levels: very unimportant, relatively unimportant, moderately important, relatively important, and extremely important. The relevant data on the importance of each teaching evaluation index were obtained through the new energy vehicle education big data processing and analysis platform. The inverse cloud generator algorithm calculates the weighted cloud $\mu_i(Kx_{\mu_i},Kn_{\mu_i},Pe_{\mu_i})$ corresponding to each evaluation index Y_i.

4.7.1. Determining the task weight cloud

For multi-task complex education $Z=\{Z_{u_1},Z_{u_2},\cdots,Z_{u_m}\}$, the weight value of the task cloud is set to $\varphi=\{\varphi_1,\varphi_2,\cdots,\varphi_k,\cdots,\varphi_m\}$ according to the effect of single task u_k on multi-task U. φ_k is the weighted cloud $\varphi_k(Kx_{\varphi_k},Kn_{\varphi_k},Pe_{\varphi_k})$ of the effect of a single assignment Z_{u_k} on the multi-task complex instruction Z. This project calculated the importance of each job based on the big data of new energy vehicle education and used reverse cloud generation technology to generate the weight cloud $\varphi_k(Kx_{\varphi_k},Kn_{\varphi_k},Pe_{\varphi_k})$ corresponding to each job u_k.

4.7.2. Determination of the single-task teaching evaluation cloud

The teaching evaluation cloud matrix was established, and the evaluation cloud $K_i^{Z_{u_k}}$ of each evaluation index of Z_{u_k} single assignment was obtained. Combined with the weight cloud μ_i of each evaluation index, the cloud operation rule was used to synthesise a single job Z_{u_k}, to obtain a single job evaluation cloud $U^{Z_{u_k}}(Kx^{Z_{u_k}},Kn^{Z_{u_k}},Pe^{Z_{u_k}})$.

$$U^{Z_{u_k}} = \frac{\sum_{i=1}^{h} K_i^{Z_{u_k}} \times \mu_i}{\sum_{i=1}^{h} \mu_i}. \tag{7}$$

4.7.3. Cloud evaluation and optimisation of multi-task complex teaching alternatives

Under the given resource constraints, s multi-task complex teaching alternative scheme for new energy vehicles was selected:

$Z_C = \{Z_{C_1}, Z_{C_2}, \cdots, Z_{C_l}, \cdots, Z_{C_s}\}$

where $Z_{C_l} = \{Z_{Zu_1,C_l}, Z_{Zu_2,C_l}, \cdots, Z_{Zu_k,C_l}, \cdots, Z_{Zu_m,C_l}\}$. Z_{C_l} is the alternative to l complex teaching. Z_{Zu_k,C_l} is the single-task teaching corresponding to the single task $u_k \in U$ in the l complex teaching alternative. The steps for evaluating and optimising s new energy vehicle teaching alternatives are as follows.

4.7.3.1. Evaluation of each single task teaching Z_{u_k, C_l}

Firstly, the evaluation cloud $K_i^{Z_{u_k,C_l}}$ and its index weight cloud μ_i corresponding to each single task teaching Z_{u_k,C_l} in alternative Z_{C_l} were determined, and then the evaluation cloud $U^{Z_{u_k,C_l}}(Kx^{Z_{u_k,C_l}}, Kn^{Z_{u_k,C_l}}, Pe^{Z_{u_k,C_l}})$ of single task teaching Z_{u_k,C_l} was calculated according to formula (6), that is:

$$U^{Z_{u_k,C_l}} = \frac{\sum_{i=1}^{h} K_i^{Z_{u_k,C_l}} \times \mu_i}{\sum_{i=1}^{h} \mu_i}. \tag{8}$$

4.7.3.2. Evaluation of multi-task complex teaching programme Z_{C_l}

According to formula (8), the evaluation cloud $U_k^{Z_{u_k,C_l}}$ corresponding to each single-task teaching Z_{u_k,C_l} in scheme Z_{C_l} was determined, and combined with its corresponding task weight cloud φ_k, and the comprehensive evaluation cloud $U^{Z_{C_l}}(Kx^{Z_{C_l}}, Kn^{Z_{C_l}}, Pe^{Z_{C_l}})$ of each multi-task complex teaching scheme Z_{C_l} was calculated according to formula (7), which is:

$$U^{Z_{C_l}} = \frac{\sum_{k=1}^{m} U_{C_l}^{Z_{u_k}} \times \varphi_k}{\sum_{k=1}^{m} \varphi_k}. \tag{9}$$

The forward cloud generator was used for image processing to complete the selection and sequencing of composite learning options for multiple tasks of new energy vehicles. Finally, composite teaching plans suitable for new energy vehicles were developed.

5. System simulation

The weights of each index of teaching evaluation of the new energy vehicle experiment course were determined. Firstly, the paper presents a weighted analysis of four primary indicators: teaching content, teaching style, teaching attitude, and teaching effect. Secondly, a weighted analysis of the sub-indices corresponding to each index type was carried out. Finally, the weighted coefficient was obtained by normalising each index (Table 2).

Table 2. New energy vehicle course teaching evaluation index weight.

Primary index	Weight	Secondary index	Weight
Teaching content	0.341	Clear explanation, systematic teaching	0.374
		Professional	0.168
		Organised	0.099
		New energy vehicle case	0.108
		Focused, difficult to explain, vivid images	0.241
		Other distinctive content	0.052
Teaching method	0.157	Use ppt, animation, news, videos, etc. for multimedia teaching	0.367
		situational teaching method	0.163
		Group report	0.186
		Teaching on the practical training platform	0.326
Teaching attitude	0.246	Class inspection and discipline inspection	0.216
		Teaching responsibilities	0.129
		Rigorous teaching and strict treatment of students	0.265
		Provide timely answers to enrich the course	0.190
		Implement moral education	0.154
		Diversification of examination methods	0.089
Teaching effect	0.256	Passion for learning	0.255
		Theoretical and technical mastery	0.415
		Teacher and student evaluation scores meet standards	0.152
		Active evaluation	0.220

From the weighting perspective, teaching content is still the most important among the first-level indicators, and the proportion of teaching attitude, teaching effect, and teaching style varies from large to small. Although these three aspects differ, their effects on teaching evaluation are different. This, in a sense, reflects that teaching evaluation should pay attention to teaching content, teaching attitude, and effect, guide teaching methods, and consider four aspects simultaneously. In the secondary indicators, the primary index is a significant proportion; for example, emphasis is placed on explaining fundamental principles and concepts in the teaching process. Emphasis was placed on the teaching of systematic knowledge. Emphasis should be placed on the use of multimedia and various practice methods. The paper should follow the teaching principles and focus on understanding students' knowledge in the education results. It is worth noting that the guiding and flexible indicators, such as novel cases, teachers' teaching characteristics, and moral education, have relatively high weights, indicating that these indicators have gradually received attention in the course evaluation of new energy vehicles.

6. Conclusion

The course architecture of new energy vehicles based on a big data environment was established. A comprehensive learning evaluation model was constructed under a big data environment. A set of teaching index clouds, index weight clouds, and task weight clouds were established based on the principle of the cloud model. The weighted group was used to evaluate and optimise multiple composite teaching. New energy vehicles were taken as the research object and typical case evaluation and optimisation were carried out to test the correctness and rationality of the research results of this project. Although the writing of the paper has been completed, there are still many shortcomings. First of all, the research on this topic only selected one school for investigation, and the coverage was narrow. In the future, the sample range selection for new energy vehicle teaching evaluation should be broader. Secondly, there are few selection indicators for consideration. More evaluation indicators should be included in the future.

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