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Research article

An edge intelligence-enhanced quantitative assessment model for implicit working gain under mobile internet of things

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Abstract: Edge intelligence refers to a novel operation mode in which intelligent algorithms are implemented in edge devices to break the limitation of computing power. In the context of big data, mobile computing has been an effective assistive tool in many cross-field areas, in which quantitative assessment of implicit working gain is typical. Relying on the strong ability of data integration provided by the Internet of Things (IoT), intelligent algorithms can be equipped into terminals to realize intelligent data analysis. This work takes the assessment of working gain in universities as the main problem scenario, an edge intelligence-enhanced quantitative assessment model for implicit working gain under mobile IoT. Based on fundamental data acquisition from deployed mobile IoT environment, all the distributed edge terminals are employed to implement machine learning algorithms to formulate a quantitative assessment model. The dataset collected from a real-world application is utilized to evaluate the performance of the proposed mobile edge computing framework, and proper performance can be obtained and observed.

Keywords: edge intelligence; mobile IoT; quantitative assessment model; mobile computing; machine learning

1. Introduction

With the deepening of educational reform in enterprise [1], enterprises pay more attention to improving the assessment model. However, the assessment model involves many factors and presents complicated changes, so it is imperative to improve implicit working gain [2]. The key to improve implicit working gain is to analyze the influencing factors. Data mining can analyze the non-linear relationship between influencing factors and assessment model [3] and mine the deep-seated problems, which is the main method to improve implicit working gain at present[4]. Artificial intelligence is a brand-new field composed of multiple subsets [5]. Machine learning can improve implicit work gain, identify implicit work content and analyze work income more accurately [6]. Some scholars believe that neural networks, computer vision, natural language processing and other methods [7], combined with edge intelligent computing methods, can better analyze the steps and methods of implicit work and comprehensively judge implicit work, so as to improve the analysis effect of gain [8]. In addition, some scholars integrate control theory with edge intelligence to reduce the amount of data processed by implicit work, improve the effect of edge analysis and improve the service experience of users. Some scholars believe that the integration of mathematical logic and edge intelligence method can reduce the processing pressure of the server, sink the processing center to the client, reduce the time delay in the processing process and improve the accuracy of calculation [9].

Literature research shows that big data technology can classify the influencing factors of the implicit working gain model, shorten the analysis time and improve the perfection rate of the appraisal model [10]. However, in classifying the influencing factors by big data technology, external uncertainties will affect the perfection of the model and the final result [11]. Some scholars have put forward a big data analysis model to judge the degree of implicit working gain in the enterprise, but there are relatively few evaluation indicators [12]. Under complex circumstances, the comprehensive judgment ability of big data analysis model decreases significantly. Therefore, some scholars put forward an edge intelligence-enhanced quantitative assessment model to analyze the implicit working gain model of enterprise and choose the corresponding improvement strategies [13]. From the above analysis, it can be seen that domestic scholars hold different opinions on the hidden work income under the mobile IoT [14]. They mainly think that the research of quantitative evaluation model of edge intelligence enhancement in this field can improve the analysis effect of hidden work income, optimize the analysis results of hidden work income and reduce the analysis amount of mobile IoT [15]. However, some scholars think that server-centered mobility analysis has more advantages in analyzing hidden work benefits. They are skeptical about the quantitative evaluation model of edge intelligence enhancement, so domestic scholars have disputes about the effectiveness of the quantitative evaluation model of edge intelligence enhancement [16]. At the same time, the research on the quantitative evaluation model of edge intelligence enhancement is mainly theoretical, lacking practical case verification and simulation analysis of results [17].

Based on this, this paper puts forward an edge intelligence-enhanced quantitative assessment model to judge and improve the implicit working gain model of enterprise and verify the model's effectiveness. Materials and methods. The main research contents of this paper are as follows. First of all, the implicit operating gain and intelligent enhancement quantitative evaluation are studied in domestic and foreign literatures, and the advantages of implicit operating gain and the feasibility of intelligent enhancement quantitative evaluation are expounded. Secondly, the implicit working gain and quantitative evaluation of intelligent enhancement are described, and the corresponding mathematical descriptions are determined; Finally, an actual case is analyzed, and the effect of intelligent enhanced quantitative evaluation is obtained. The influence of this method and model on cost and feasibility is studied, and the effectiveness of the model proposed in this paper is verified.

2. Materials and methods

2.1. Big data theory

Big data theory mainly originates from Web 2.0, a general term for massive data [18]. The original processing technology and method can not analyze data quickly and effectively [19]. At the same time, big data requires high machine performance, which requires massive data computing power. Big data mining software is mainly Hadoop, spark, storm, etc. In order to better study the implicit working gain model of enterprise, this paper refers to the related literature on edge intelligence enhancement, improves the clustering algorithm, puts forward a quantitative model of edge intelligence enhancement, and describes the related contents mathematically.

Quantitative analysis definition 1: Referring to the quantitative analysis theory,Assuming the sample of the enterprise implicit working gain model $X=(x_i \mid i=1,\cdots,n)$, then the implicit working gain index is d_i, and the influence expectation of each index on the model is q_i. The implicit working gain function $K(d_i,q_i,b_i)$ maps all implicit working gain indicators into the space $L(o_i)$, realizes the standardization of indicators, and judges the mapping distance of implicit working gain indicators S to minimize their values. The specific judgment is shown in formula (1).

$$S=w\cdot L(o_i)+K(d_i,q_i,b_i)\lambda \tag{1}$$

Among them, w is the weight of mapping and λ the threshold of implicit working gain. At that time $|S|=1$, the sample distance $\|w\|$ is the smallest, and the weight at this time is $\|w\|/2$. Implicit working gain definition 2: Referring to the theory of economic gain in economic management, If the distribution degree of implicit working gain is ξ_i ,evenly distributed in [0, 1], samples are reasonably classified and the threshold value of implicit working gain is distributed in $[1,+\infty]$. At this time, the calculation of S is shown in formula (2).

$$\begin{cases} \max S=w\cdot K(d_i,q_i,b_i)\Leftrightarrow \lambda\bullet\sum\xi_i \\ w\pm K(d_i,q_i,b_i)\in[0,+\infty] \end{cases} \tag{2}$$

Mobile IoT definition 3: According to the information transmission mechanism of mobile Internet, If $K(d_i,q_i,b_i)=\varphi(d_i)\cdot\varphi(q_i)$ is a function, it is shown in formula (3).

$$\begin{cases} \max L(o)=\sum\theta_i \Leftrightarrow \sum o_i K(d_i,q_i,b_i \mid \gamma) \\ o_i \rightleftarrows d_i \rightleftarrows z_i \end{cases} \tag{3}$$

Among them, θ represents the implicit working gain index and mapping point and γ reflects the spatial distribution degree of implicit working gain. Therefore, the index θ and γ in big data theory is the key to judge the perfection rate of implicit working gain in enterprise, and it is also the main index of optimization.

2.2. Data mining techniques

At initialization, the number of implicit working gains and appraisal models is the same. Different implicit working gain status is affected by different factors. Firstly, the implicit working gain indicators of the enterprise are randomly generated, and the influencing factors with better fitness value are selected, and the implicit working gain is analyzed with this influencing factor as the core, and the "secondary" factors, about 1/3, are eliminated through screening; then, using recurrence strategy to choose the most prominent factors affecting the performance model, and giving corresponding weights; finally, give up the influencing factors that do not meet the threshold, and analyze other implicit working gain indicators. Assuming that the initial number of implicit working gain indicators and appraisal models is *n*, and the random position of implicit working gain indicators is $L=(o_i)$, which x_i, y_i represents the complexity and depth of implicit working gain and z_i represents the implicit working gain indicators of different models, then the initial position of implicit working gains is shown in formula (4).

$$L_i(o_i)=w\cdot\lambda\cdot K(d_i,q_i,b_i)\Rightarrow z_i\cdot rand(0,1)K[(x_{j\max}-y_{j\min})k] \tag{4}$$

Among them, x_i , y_i and z_i are random crisis of enterprise implicit working gain and $x_{j\max}$ is the most important factors and $x_{j\min}$ the least important factors, $rand(0,1)$ are random numbers within the range of [0, 1], and k is the constant coefficient of the implicit working gain index. Randomly select implicit working gain indicators and cross-judge to update the position of implicit working gain indicators. Under the constraint of fitness, judge the influence degree of the index, as shown in formula (5).

$$L_i(o_i)=w\cdot\varphi_{ijz}\cdot\sum K(d_i,q_i,b_i)/\sum\lambda\bullet K(d_i,q_i,b_i|k) \tag{5}$$

Among them, $o\in[0,n/2]$, $i\in[0,n]$, $\varphi_{ijz}\in(-1,1)$, and $k\neq i$. The in-depth mining of performance examination indicators is based on probability p_i, and the best implicit working gain indicators are obtained through probability calculation. The neighborhood judgment of the implicit working gain indicators is carried out to obtain the implicit working gain meeting the threshold. The judgment process is shown in formula (6).

$$p_i=K(d_i,q_i,b_i)/\sum_{i,j,k}^{n}[K(\Delta o_i)|k] \tag{6}$$

Among them, it is a moderate function among different implicit working gains. If the implicit working gain of the enterprise has not got the possible implicit working gain after the preset cycle, that is, the judgment matrix is 0, then give up the search for implicit working gain and dig deep into the existing implicit working gain [20]. At the same time, according to formula (4), a new implicit working gain index is randomly generated here for the subsequent judgment. Adjustment of implicit working gain in an enterprise. In the initial stage, if the judgment of the implicit working gain cannot guarantee comprehensiveness, it may fall into the trap of the previous judgment and reduce the overall performance of the judgment results of the implicit working gain [21]. Therefore, in analyzing the implicit working gain, we should try our best to expand the judgment scope, narrow the judgment scope near the main influencing factors of the model, and constantly adjust the indicators to improve the perfection rate of the model. Some scholars set the adjustment rate of implicit working gain ϕ to linear adjustment, but the recognition rate of main influencing factors is low. In order to make up for the deficiency of the above analysis, this paper introduces an adjustment factor ν, and the judgment result is shown in formula (7).

$$\phi = \min \sum \Delta \nu_i \bullet e^{-F(x_i, y_i, z_i)} \tag{7}$$

Among them $\Delta \nu_i$ is the analysis of i-times influencing factors, $F(x_i, y_i, z_i)$ the coincidence degree between i-times influencing factors, and model adjustment. The angle of key data search and profound mining changes, and the results are shown in formula (8).

$$\Delta L\ (x_i, y_i, z_i) = w \cdot K(d_i, q_i, b_i) + \lambda \nu_{ijz} K(\Delta d_{ik}, \Delta q_{ik}, \Delta b_{ik}) \tag{8}$$

From formula (7), $F(x_i, y_i, z_i)$ it can be seen that in the initial stage, the value ν is relatively small and the value is relatively large, so the search range of crucial data is expanded [22], so as to avoid falling into local "traps" and keep the comprehensiveness of assessment model analysis. In the later stage of judgment, the value $F(x_i, y_i, z_i)$ is relatively large and ν is relatively small, so it is necessary to strengthen the search of relevant data, improve the depth of data mining, and enhance the judgment effect of enterprise implicit working gain.

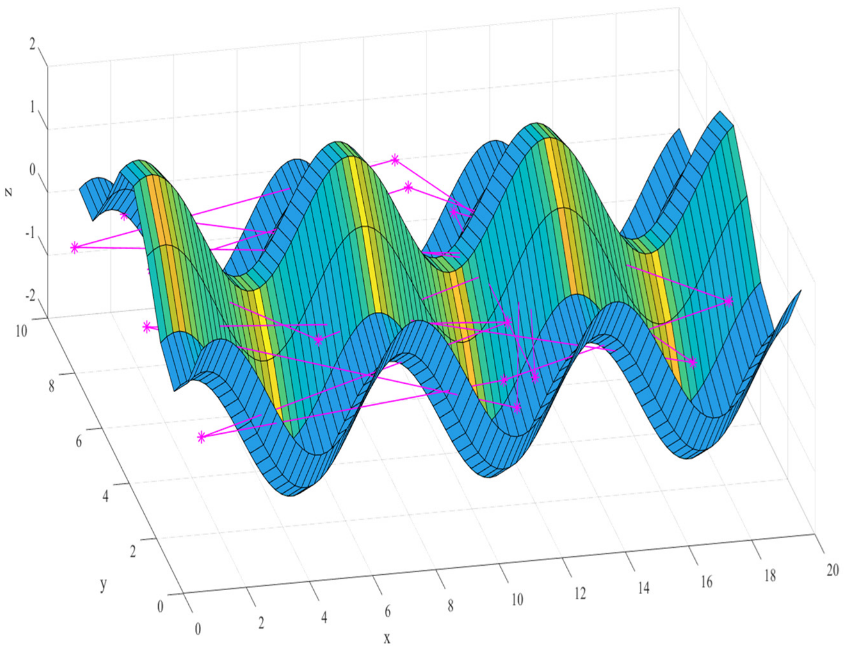

Figure 1. Adjustment effect of enterprise implicit working gain.

The adjustment of implicit working gain in enterprise can improve the accuracy of perfecting the model. As can be seen from Figure 1, the extreme value of data analysis is on the data plane in the big data sample. Therefore, the sample adjustment of implicit working gain in enterprise meets the data analysis requirements and can be used for later data analysis—introducing regulatory factors. When a specific implicit working gain index has been comprehensively analyzed for many times and reached the analysis limit, the key data search will be changed into deep mining, looking for new implicit working gain improvement strategies and judging new influencing factors [23]. Due to the strong randomness and poor anti-disturbance ability of implicit working gain in the enterprise, errors will appear in the early stage of appraisal model analysis. In order to reduce the probability of implicit working gain error, this paper introduces the Cauchy factor to reduce the uncertainty of implicit working gain through the probability density function, which helps to reduce the error of implicit working gain in an enterprise. The calculation formula of the adjustment factor is as shown in formula (9).

$$L(x_i, y_i, z_i) = \frac{\frac{F(x_i, y_i, z_i)}{t}}{\pi \sum_{i,k=1}^{+\infty} \frac{F(x_i, y_i, z_i)}{\sum t} + \left|K(\Delta o)\right|^2} \tag{9}$$

When $\frac{F(x_i, y_i, z_i)}{\kappa}$ is 1, $F(x_i, y_i, z_i)$ can be expressed by Cauthy (0, 1). At that time, the external uncertainty representing implicit working gain was the highest, otherwise, the uncertainty was the lowest [24]. Because the two sides of Cauthy (0, 1) tend to extreme value slowly, its distribution speed is lower than Gauss (0, 1), thus reducing the uncertainty of implicit working gain. Moreover, the peak value of Cauthy (0, 1) is smaller than that of Gauss (0, 1), which weakens the influence of other indexes.

2.3. Mobile IoT strategy analysis

The rationality of the choice of mobile IoT strategy is the main index to measure edge intelligence-enhanced quantitative assessment model. The analysis of enterprise implicit working gain among key data search, in-depth mining and deep calculation [25] can measure not only the relationship between implicit working gain and the Improvement of the appraisal model but also improve the accuracy of model improvement. From formula (8), we can see that when judging the influencing factors of implicit working gain in the initial stage, we pay great attention to the analysis of comprehensive factors, and when judging the influencing factors in the later stage, we pay attention to the Improvement of implicit working gain. At the same time, choose different model improvement strategies according to different implicit working gains. At present, besides edge intelligence-enhanced quantitative assessment model, there are other improved strategies.

1) The improvement strategy of individual implicit working gain, as shown in formula (11)

$$\Delta L_i(x_i, y_i, z_i) = \sum_t \Delta L_{i-1}(x_i, y_i, z_{i-1}) \tag{11}$$

2) Integrated deep computing strategy, as shown in formula (12)

$$\Delta L_i(x_i, y_i, z_i) = \sum_t \Delta L_{i-1}(o) + Cauthy(0,1) \tag{12}$$

3) Indicator improvement strategy, as shown in formula (13)

$$\Delta L_i(o) = \sum_{i=1,t}^{n/2} \Delta L_{i-1}(o) \cdot [g \max K(\cdot) \forall p \max K(\cdot)] \tag{13}$$

4) Multi-angle mobile IoT strategy, as shown in formula (14)

$$\Delta L_i(o_i)=\sum_t \Delta L_{i-1}(o_{i-1}) \Leftrightarrow K(\Delta o_{i-1k}) \tag{14}$$

Among them, T is the perfect time of implicit working gain.

In this paper, edge intelligence-enhanced quantitative assessment model is improved in two aspects: on the one hand, mapping weight w and mapping threshold λ are set every time the implicit working gain is analyzed [26]. At the same time, edge intelligence-enhanced quantitative assessment model is randomly selected from five improvement strategies, and the implicit working gain is improved many times. In the later stage of implicit working gain judgment, gradually reduce the judgment space, make neighborhood judgment, keep the diversity of implicit working gain judgment in enterprise, and improve the comprehensiveness of judgment. On the other hand, it balances the comprehensive judgment of enterprise implicit working gain with the perfection of individual implicit working gain, and integrates renewal factor Δv_i , moderate function $F(x_i, y_i, z_i)$ and *Lagrangian* multiplier function to judge the performance model more accurately-the Synergy between implicit working gain indicators of different universities. Collaborative analysis of influencing factors of implicit working gain in enterprise is the main way to improve the implicit working gain. Based on the analysis of implicit working gain indicators in enterprise, this model constructs a distributed collaborative mobile IoT strategy [27]. Different subsets adopt collaborative models to improve strategies, complex indicators and operations. The implicit working gain of enterprise is randomly divided into five subsets, and each subset represents a subspace. The subset will randomly select different collaborative analysis models in each iterative process. After each implicit working gain is comprehensively analyzed, compare the fitness value of different subsets and the complexity of implicit working gain, and record the best model; Other subsets gather to the best perfect strategy to improve the judgment efficiency of implicit working gain indicators.

2.4. Index summary of implicit operating gain

Given the above analysis, the index of implicit operating gain is summarized, and the results are shown in Table 1.

Table 1. Index of implicit operating gain.

Index	Description	Index	Description
d_i	Indicator of implicit operating gain in units, units: piece	p_i	Possibility of the impact of indicators, units:%
x_i	Depth of analysis, units:%	v	Correlation of different indicators, units:%
y_i	Analysis complexity, units:%	λ	Threshold of indicators, Unit: Each index unit
z_i	Index processing difficulty, units:%	w	Weight of indicators, Unit:%

2.5. Steps to improve the implicit working gain of enterprise based on edge intelligence-enhanced quantitative assessment model

The basic idea of the edge intelligence-enhanced quantitative assessment model is to optimize the initial value and threshold of complex implicit working gain by using various collaborative model improvement strategies [28], obtain the main impact indicators of implicit working gain, and improve the implicit working gain. The implementation steps of this model are shown in Figure 2 below:

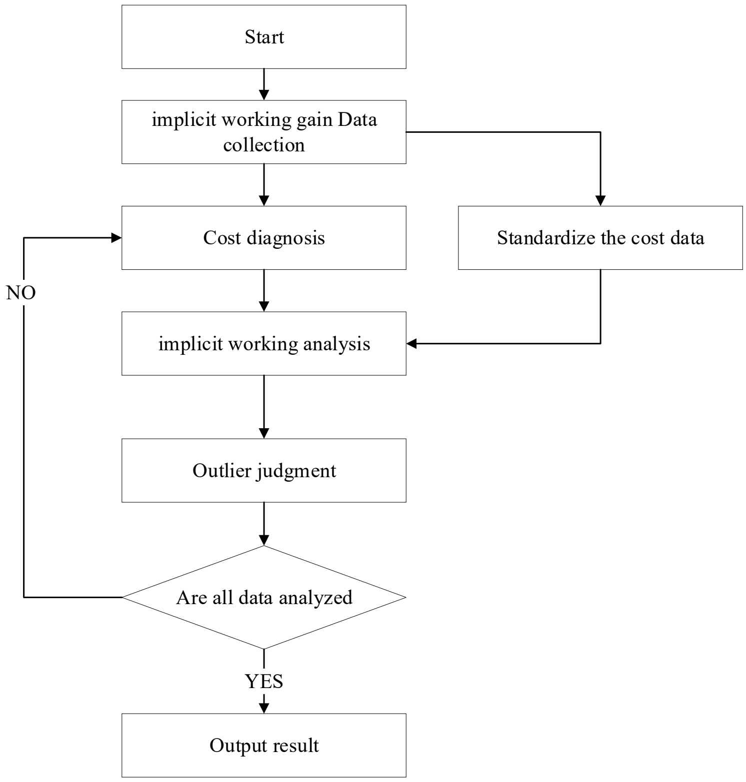

Figure 2. The implementation process of implicit working gain in enterprise.

Step 1: Determine the structure and uncertainty of implicit working gain. According to the characteristics of practical problems, determine the non-linear distribution structure of implicit working gain, as well as uncertainty, this paper the uncertainty of enterprise implicit working gainis $\gamma = 5$ .Initialize the review model. According to the relevant indicators, the implicit working gain of enterprise is initialized. The number of implicit working gain in the enterprise is n=30, which is consistent with the number of implicit working gain in enterprise, $\Delta \nu_i \in [0.2, 0.8]$ and $Cauthy(0,1) \in [0.32, 0.72]$, the number of iterations is m=30.

Step 2: Determine the fitness function. Using big data theory, the enterprise's implicit working gain indicators are randomly generated and mapped to two-dimensional space, and the initial mapping vector weight w and mapping threshold λ are obtained. According to the implicit working gain requirements, $w = 0.32$ and $\lambda = 0.83$. Through formulas (3)–(7), the implicit working gain of enterprise is improved, and the fitness value of each implicit working gain index is judged. Judge the implicit working gain and the best improvement strategy of implicit working gain indicators. Initial enterprise implicit working gain indicators are divided into five sub-sets to obtain fitness, and compare the best strategy of implicit working gain and sub-implicit working gain indicators of the best strategy.

Step 3: Improvement strategy and deep calculation update iteration of implicit working gain indicators. According to the change of implicit working gain, the Cauchy factor is adjusted in the implicit working gain of five sub-universities, and strategies are randomly selected from five strategies. According to Formula (2) and Formula (7), penalty factor C and inertia weight $\Delta \nu_i$ are integrated.

Collaborative analysis of implicit working gain of sub-universities. After a implicit working gain index analysis, select the best implicit working gain, and share the improvement strategy of this model with other sub-universities' implicit working gain indicators, and analyze the neighborhood appraisal model to get the final improvement model.

Step 4: Judge whether the implicit working gain index reaches the maximum value *m* and whether the iteration times reach *M*. If it has been reached, repeat steps 1–3, otherwise stop the analysis of implicit working gain, and return to the threshold, weight and best mobile IoT strategy.

3. Empirical analysis

3.1. Model performance analysis

In order to further verify the performance of edge intelligence-enhanced quantitative assessment model, four benchmark functions are selected: rastring, sphere, ackley and girewank. The test process is as follows.

1) Rastring function, and the result is shown in formula (15)

$$f(x)=\sum_{i=1}\frac{x_i^{\ 2}}{10}+1 \tag{15}$$

2) Sphere function, and the result is shown in formula (16)

$$f(x)=\sum_{i=1}\sqrt{x_i^{\ 2}} \tag{16}$$

3) Ackley function, and the result is shown in formula (17)

$$f(x)=\frac{e}{20}+\left|\mathrm{e}^{\frac{x_i}{5}\sqrt{\frac{1}{n}}}\right| \tag{17}$$

4) Girewank function, and the result is shown in formula (18)

$$f(x)=k+\sum_{i=1}\frac{x_i^{\ 2}}{300} \tag{18}$$

where, $|x_i|\in[0,300]$, *i* is 1, 2. Get the minimum value 0 at (0, 1). The index setting of simulation experiment in this paper: the total number of implicit working gain indexes is 50, the iteration times are 50, the analysis limit is 20 times, the maximum update experience $\Delta\nu_{\max}=2$, the minimum experience $\Delta\nu_{\min}=0.4$, the complexity $\gamma=0.7$ is that each group of experiments is carried out independently, and the result is the average of 50 iterations. The operation results of the four test functions are shown in Table 2.

As can be seen from Table 1, the edge intelligence-enhanced quantitative assessment model is superior to traditional examination technology, with a higher matching degree and more theoretical best strategies. Moreover, the value range, average value, and judgment error of the edge intelligence-enhanced quantitative assessment model are smaller than those of traditional examination technology.

Table 2. Results of different test functions.

Function	Method	Maximum value	Minimum value	Average value	Standard deviation	Matching degree	Theoretical optimal strategy number
Rastring	Edge intelligence-enhanced quantitative assessment model	1.313	1.343	1.429	0.739	93%	2
	Traditional assessment technology	0.413	0.243	0.329	0.388	82%	1
Sphere	Edge intelligence-enhanced quantitative assessment model	1.481	1.429	1.429	0.344	98%	3
	Traditional assessment technology	0.311	0.323	0.423	0.142	90%	1
Ackley	Edge intelligence-enhanced quantitative assessment model	1.849	1.343	1.429	1.381	96%	3
	Traditional assessment technology	0.481	0.312	0.313	0.338	92%	1

3.2. Feasibility, cost analysis

In order to verify the performance of the edge intelligence-enhanced quantitative assessment model more intuitively and judge the perfection of implicit working gain by this technology, the following analysis graphs are given, as shown in Figures 3 to 5.

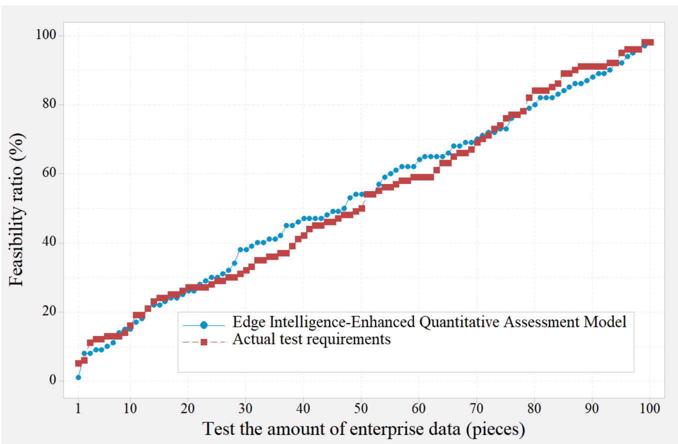

Figure 3. Feasibility analysis of quantitative evaluation model for edge intelligence enhancement.

It can be seen from Figure 3 that there is little difference between the analysis results of the quantitative evaluation model of edge intelligence enhancement and the actual test requirements, and the two show cross changes, indicating that the test results of the two methods are similar. In addition, the variation range of the two methods is small, which shows that the two methods have good analysis results in implicit operating gain analysis. Cost-benefit is also an important index of implicit work gain analysis, so cost analysis of implicit work gain is carried out and compared with actual cost accounting. The results are shown in Figure 4.

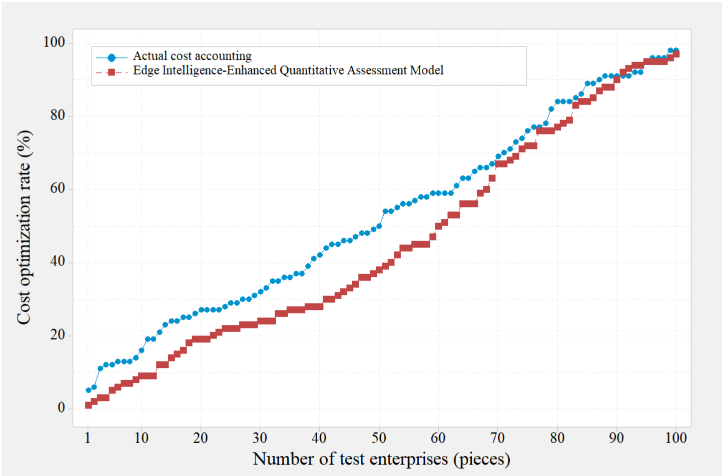

Figure 4. Cost-benefit of quantitative evaluation model for edge intelligence enhancement.

It can be seen from Figure 4 that the cost optimization ratio of the quantitative evaluation model enhanced by edge intelligence is less than the actual cost accounting, but in 90–100 enterprises, the results of the two are merged. Therefore, the quantitative evaluation model of edge intelligence enhancement is better for a large number of enterprises, but worse for a small number of enterprises. The main reason is that cost accounting is an enterprise in an industry, and the number of enterprise accounting in this industry is large, so the quantitative evaluation model enhanced by edge intelligence plays an obvious role in enterprise cost accounting. Based on the results in Figure 3 and Figure 4, the implicit operating gain is comprehensively analyzed, and the effects of the two accounting methods are compared. The results are shown in Figure 5.

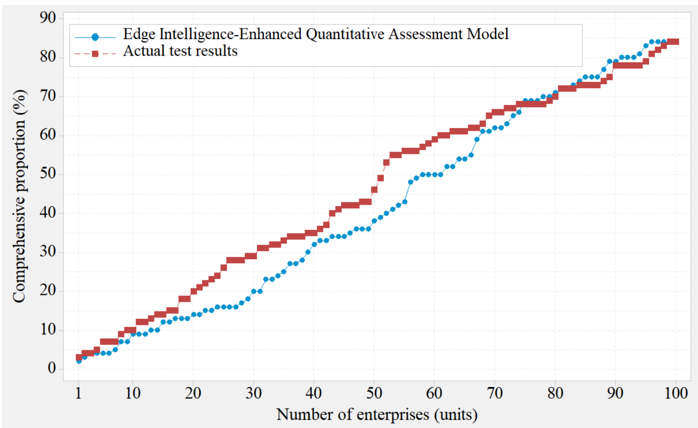

Figure 5. Comprehensive optimization of quantitative evaluation model for edge intelligence enhancement.

It can be seen from Figure 5 that the comprehensive optimization results of the quantitative evaluation model enhanced by edge intelligence are basically consistent with the actual test results. Although there are small differences, the overall results are close. At the same time, there is a difference between the change trend of the quantitative evaluation model of edge intelligence enhancement and the actual test, which is mainly caused by external interference. On the whole, the quantitative evaluation model of edge intelligence enhancement is better for the comprehensive analysis of implicit working gain.

3.3. Experimental assessment model processing

In this paper, three universities' implicit working gain indicators are selected as research samples, and the collection time is from December 30, 2021 to May 10, 2022, with a sample number of 1123. After preliminary screening and sorting of assessment indicators, 221 assessment indicators were obtained. According to the requirements and standards of implicit working gain by the state and universities, the implicit working gain is classified into four categories: incomplete model, incomplete index, unbalanced model and unreasonable coverage of model. This paper judges the accuracy of the results according to the theoretical judgment and practical verification. In order to avoid redundancy in the collection review model, call the sharing function to replace the repeated review model and keep the uncertainty of the collection review model. The results are shown in Table 3.

Table 3. Collect the types and proportion of implicit working gains.

Classification of assessment model	Number of assessment models (pieces)	Proportion (%)
Incomplete model	41	22.1
Incomplete indicators	33	15.85
Unbalanced model	21	11.73
The coverage of the model is unreasonable	100	50.32

The first 1/2 of the total number of samples is taken as theoretical samples, and the last 1/2 is taken as actual samples, and the results are compared.

3.4. Experimental results

According to the experimental situation, the data structure of the enterprise implicit working gain is 11-15-20, enterprise implicit working gain is $Cauthy(0,1) = 0.32$ the maximum iteration times is M=50, and other indicators are set the same. This paper puts forward the classification results of implicit working gain of enterprise by edge intelligence-enhanced quantitative assessment model, as shown in Figure 6.

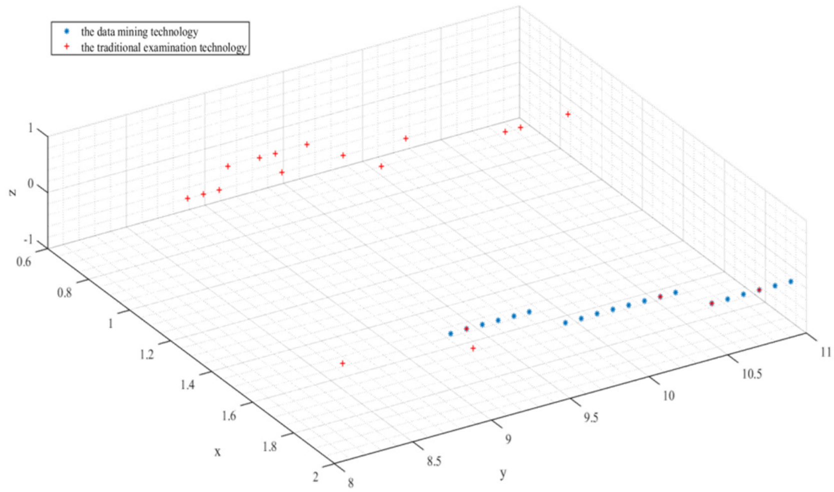

Figure 6. Classification results of samples of implicit working gain in enterprise.

Through comparative analysis, we can see that the sample classification of the edge intelligence-enhanced quantitative assessment model is discrete, closer to the actual classification and comparative distribution of enterprise implicit working gain. At the same time, the traditional examination technology is concentrated on classifying enterprise implicit working gain, which cannot meet the needs of actual classification. In addition, the sample distribution of the edge intelligence-enhanced quantitative assessment model is not affected by external factors, while the sample distribution of traditional examination technology is more concentrated by uncertainty. The reason is that edge intelligence-enhanced quantitative assessment model incorporates coefficients and factors, maps implicit working gain indicators to two-dimensional space, and realizes standardized processing of index data. Comparing the evaluation effects of different methods on the implicit working gain of enterprise, they are mainly: traditional examination technology, big data theory combined with traditional examination technology, big data technology, and edge intelligence-enhanced quantitative assessment model. The results are shown in Figures 7–8.

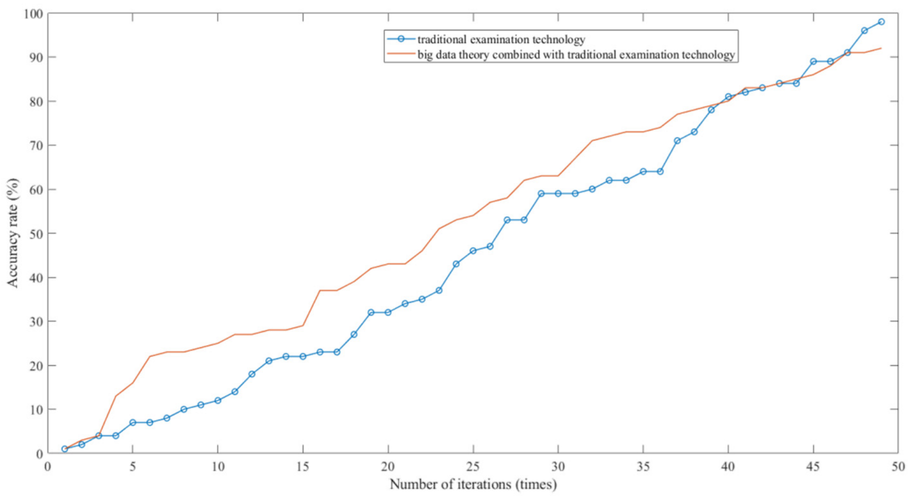

Figure 7. Comparison of accuracy values of two different methods.

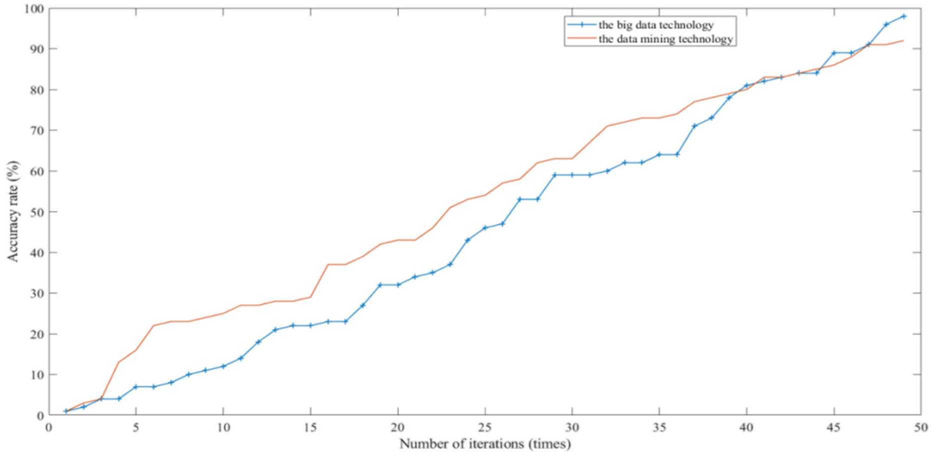

Figure 8. Comparison of accuracy values of two different methods.

As can be seen from the above Figure7 and Figure8, the fitness value of edge intelligence-enhanced quantitative assessment model is the highest, reaching the limit at the earliest. Under the same uncertainty, the stability of edge intelligence-enhanced quantitative assessment model is higher, followed by traditional examination technology, big data theory combined with edge intelligence-enhanced quantitative assessment model and big data technology. The reason is that edge intelligence-enhanced quantitative assessment model reduces the influence of uncertainty on judgment results, and edge intelligence-enhanced quantitative assessment model provides different model improvement strategies to improve the accuracy of implicit working gain improvement results, which is consistent with relevant research [29]. From the main influencing factors, this paper analyzes the accuracy of implicit working gain by different technologies, and the results are shown in Table 4.

Table 4. Perfection rate of assessment model by different methods.

Classification of the assessment model	Edge intelligence-enhanced quantitative assessment model	Traditional examination technology	Big data theory combined with traditional examination technology	Big data technology
Incomplete model	99.34	98.33	97.32	96.31
Incomplete indicators	99.37	98.32	98.37	98.30
Incomplete indicators	99.31	95.34	95.33	92.31
The coverage of the model is unreasonable	99.34	97.32	94.33	95.36

As can be seen from Table 4, the perfection rate of the implicit working gain of the edge intelligence-enhanced quantitative assessment model is high, and the accuracy rate does not change with the type of implicit working gain. The main reason is that analyzing samples by adjustment factors makes its continuous judgment time shorter and can change the mobile IoT strategy more flexibly. Therefore, an edge intelligence-enhanced quantitative assessment model can not only reduce the impact of uncertainty on the improvement rate of the model but also improve the improvement rate of the implicit working gain.

4. Conclusions

This paper puts forward a perfect model of enterprise implicit working gain based on big data theory and edge intelligence-enhanced quantitative assessment model. By setting thresholds, weights, and collaborative methods, we can help enterprise choose reasonable model improvement strategies. Edge intelligence-enhanced quantitative assessment model can classify samples discretely [30], which makes the sample distribution closer to the actual distribution and improves the accuracy of analysis results. MATLAB simulation results show that edge intelligence-enhanced quantitative assessment model has higher judgment accuracy, reduces the impact of uncertainty and model problems on the results, and has a higher improvement rate of implicit working again in the enterprise. However, in the implicit operating gain analysis process, there are some limitations, especially the interference factors of implicit operating gain. Because implicit work gain analysis will be affected by policies, industry development and long-term and short-term strategies of enterprises, uncertain factors will have a particular impact on the results. Therefore, in future research, the influence of interference factors on the results will be increased.

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