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Research Article

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Intelligent financial decision support system based on big data

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Abstract: In the era of big data, data information has exploded, and all walks of life are impacted by big data. The arrival of big data provides the possibility for the realization of intelligent financial analysis of enterprises. At present, most enterprises' financial analysis and decision-making based on the analysis results are mainly based on human resources, with poor automation and obvious problems in efficiency and error. In order to help the senior management of enterprises to conduct scientific and effective management, the study uses big data web crawler technology and ETL technology to process data and build an intelligent financial decision support system integrating big data together with Internet plus platform. J Group in S Province is taken as an example to study the effect before and after the application of intelligent financial decision support system. The results show that the crawler technology can monitor the basic data and the big data in the industry in real time, and improve the accuracy of decision-making. Through the intelligent financial decision support system which integrates big data, the core indexes such as profit, net asset return, and accounts receivable of the enterprises can be clearly displayed. The system can query the causes of financial changes hidden behind the financial data. Through the intelligent financial decision support system, it is found that the asset liability ratio, current assets growth rate, operating income growth rate, and financial expenses of J Group are 55.27, 10.38, 20.28%, and 1,974 million RMB, respectively. The growth rate of real sales income of J Group is 0.63%, which is 31.27% less than the excellent value of the industry 31.90%. After adopting the intelligent financial decision support system, the monthly financial statements of the enterprises increase significantly, and the monthly report analysis time decreases. The maximum number of financial statements received by the Group per month is 332, and the processing time at this time is only 2 h. According to the results, it can be seen that the intelligent financial decision support system integrating big data as the research result can effectively improve the financial management level of enterprises, improve the usefulness of financial decision-making, and make practical contributions to the field of corporate financial decision-making.

Keyword: big data, crawler technology, intelligent finance, decision support

1 Introduction

Intelligent financial decision support system is a human-computer interaction system based on modern management science theories that uses computer technology to carry out the financial analysis, financial control, and financial forecasting of enterprises [1]. At present, most enterprises' financial analysis and decision-making based on the analysis results are mainly based on human resources, with poor automation and obvious problems in efficiency and error. The remedy measures for these shortcomings are one of the main research contents in the field of corporate financial analysis. This research is also to improve the

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company's financial analysis and decision-making system, improve the degree of automation and increase the efficiency of analysis. With the development of data processing technology, big data web crawler technology has emerged, which has substantially improved the ability of enterprises to process big data [2]. At the same time, the development of artificial intelligence and expert systems also improves the informatization and networking of modern financial management to a certain extent, prompting the intelligence of enterprise financial management [3]. In the context of big data, data have become the core asset of enterprises, and artificial intelligence technology can realize multi-dimensional analysis of data and help managers to dig out the information hidden in financial data, so intelligent financial decision support system has become the development trend of enterprise financial informatization [4,5]. The relevant decision makers of enterprises should focus on semi-structured and unstructured enterprise financial data, set heterogeneous data from multiple sources in one data warehouse, and combine artificial intelligence algorithms to constitute a knowledge base to assist enterprise management decisions, and finally display the information in a visual interface. The contribution of this study is to bring practical research results to the field of financial analysis and decision-making of the company and increase work efficiency.

2 Related works

Under the influence of big data, the current data technology used in the processing and analysis of corporate financial data is constantly advancing. A number of studies with implications for the computerization of corporate financial data and the processing of big data already exist [6]. Jin and his team analyzed the historical data from financial institutions. The analysis tools included non-statistical algorithms such as random forest and logistic regression, and a loan default model was built based on the analysis results. The model was designed to effectively assess and identify bad debt risk before lending. The experimental results showed that the importance ranking of features based on random forest could effectively improve the accuracy of loan risk judgment [7]. Zhu and Yang introduced the techniques and related strategies of big data analytics to the bank's internal financial processes. The study found that big data elements had a significant impact on both the stability and financial performance of the bank's internal processes. Finally, they used the results of big data analysis to propose a strategy to reduce the stress in the bank's operating environment, which effectively increased the bank's financial performance [8]. Tavera Romero et al. led his group to propose a multiple customer data management system based on big data and business intelligence. The results of the study showed that the system can effectively organize customer data and improve the financial performance of the firm [9]. Xiao and Ke proposed a financial data mining algorithm that combines big data and artificial intelligence. The algorithm is able to mine effective data in financial markets to optimize asset pricing and management [10].

According to the results compiled from the literature, the current field of financial research has noticed the impact of big data on the industry and the market, and is actively applying various new technologies to the field of financial research. Most of the relevant studies so far focus on the analysis of a specific financial indicator and cannot automate the analysis and decision making of the overall financial situation of the enterprise in a simple way. Therefore, this study proposes an intelligent financial decision support system that incorporates big data.

3 Construction of intelligent financial decision support system integrating big data

3.1 Web big data crawler technology and ETL data process

The user gives instructions through the computer, and the web crawler technology starts acting according to the accepted instructions and automatically collects the target data [11]. Web crawler technology has the characteristics of real-time collection and automatic collection, the former guaranteeing the timeliness of the data and the latter guaranteeing the accuracy and integrity of the data, which is conducive to the diverse storage and analysis of the data [12]. In order to improve resource utilization, this study proposes a web scraping algorithm and applies it to a financial decision support system. During the use of web crawling technology, important information on web pages should be extracted. The study uses the best-first search method to judge topic similarity.

$$\mathrm{TF}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}, \tag{1}$$

where term frequency (TF) refers to the frequency of a specific word in the selected text, which is mainly used to increase the weight of keywords. $n_{i,j}$ indicates the occurrence frequency of a word t_i in the text d_j, so the sum of all words in the text can be represented by $\sum_k n_{k,j}$.

$$\mathrm{IDF}_i = \log\frac{|D|}{|\{j : t_i \in d_i\}| + 1}, \tag{2}$$

where IDF denotes the reverse document frequency, which is used to reduce the topic weight of public words [13]. $|D|$ denotes the total number of corpus documents, and the number of documents containing the word t_i is denoted by $|\{j : t_i \in d_i\}|$.

$$w_{i,j} = \mathrm{TF}_{i,j} \times \mathrm{IDF}_i, \tag{3}$$

where TF × IDF refers to the weight $w_{i,j}$ of the word, which is mainly used for the ranking of weights, while obtaining Top-N, which acts as the keyword of the text. The calculation of topic relevance is performed by the vector space model algorithm, so that the vector space dimension is the number of keywords n. At this time, the weights of different keywords k are the values of the corresponding different dimensions [14].

$$\partial = \sum_{k\in q} f_{k,q} = (w_1, w_2, \ldots, w_n), \tag{4}$$

where the weight of specific keyword k in topic q is represented by $f_{k,q}$. If p indicates the page, the keyword with the highest frequency of occurrence is selected as the target, and the corresponding frequency is expressed by $x_i = 1$.

$$\beta = \sum_{k\in p} f_{k,p} = (x_1w_1, x_1w_2, \ldots, x_1w_n), \tag{5}$$

which is the topic-defining equation of page p, where x_1w_i is the value of a single dimension in the corresponding vector within the page.

$$\mathrm{Sim}(q, p) = \frac{\sum_{k\in q\cap p} f_{k,q}\, f_{k,p}}{\sqrt{\sum_{k\in q} f_{k,q}{}^2}\,\sqrt{\sum_{k\in q} f_{k,q}{}^2}} = \cos\langle \alpha, \beta\rangle = \frac{x_1w_1{}^2 + x_2w_2{}^2 + \ldots + x_nw_n{}^2}{\sqrt{w_1{}^2 + w_2{}^2 + \ldots + w_n{}^2}\,\sqrt{x_1{}^2w_1{}^2 + x_2{}^2w_2{}^2 + \ldots + x_n{}^2w_n{}^2}}. \tag{6}$$

Formula (6) is an expression for the usage harvest rate, which is the ratio of the number of topic-related pages to the number of pages that have been extracted. This index is mainly used to judge the relevance of pages. The meaning of each letter in it represents the same as the description of the above formulas. Considering the real situation, a threshold r is set, and when $\cos\langle\alpha, \beta\rangle \geq r$, the page is relevant to the topic.

In the ETL of data warehouse, "E" refers to "Extracting data," "T" refers to "Transforming data," and "L" refers to "Loading data." The ETL also includes "Cleaning " which means "Cleaning data" [15]. Data warehouse can be divided into client layer (querying and customizing reports), server layer (filtering system junk data, transforming data formats), and online analysis server layer (simplifying processes and increasing data transfer quality) [16].

Figure 1 shows the schematic diagram of the ETL architecture of the data warehouse of J Group company. The source data system includes enterprise accounting system, reporting system, financial sharing system, UFIDA software, Kingdee software, and Longchao software. After the data are extracted, transformed, cleaned, loaded, and other series of operations are completed, they enter the data warehouse sharing platform of the

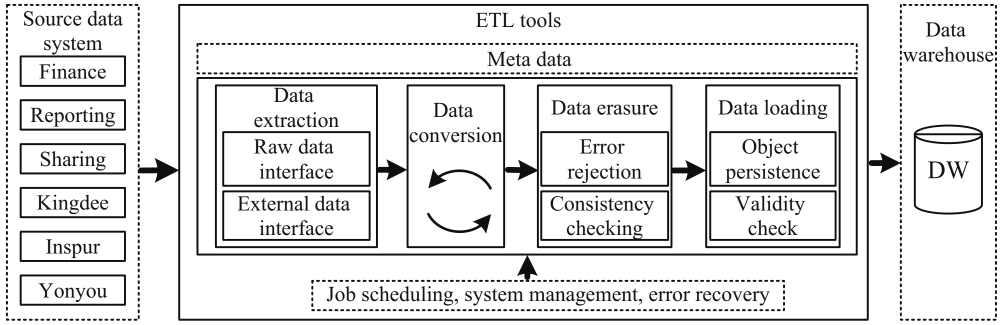

Figure 1: ETL architecture diagram.

group's operation distance vehicle together with the external data obtained through the network big data crawler system. If the data are stored in a relational database and the data are structured, the extraction of the data is completed using SOL statements, and the target data are extracted into a temporary database through metadata mapping rules, combined with a SQL language generator, and processed and output to the target database [17,18].

3.2 Intelligent financial decision support system architecture

Intelligent financial decision support system is a technology that combines computer artificial intelligence with management science. It achieves the construction of a working environment with a combination of knowledge, initiative, and information processing capabilities by means of artificial intelligence dialogues to provide decision support work for corporate decision makers and substantially improve the management of dry-level managers [19,20]. The study selected 50 enterprises in province S for analysis, 36 of which belong to groups, 7 to shares/units, 3 to group finance companies, 3 to administrative institutions, and 1 is of banking nature.

Table 1 shows the demand analysis results of 50 enterprises in S province for intelligent financial decision support system. The above 50 enterprises have the strongest demand for data analysis, followed by demand for industry benchmarking, demand for processing and analysis of external big data, demand for smart financial analysis report, demand for risk warning, demand for artificial intelligence modeling, demand for intelligent interaction, and demand for self-service. Among them, industry benchmarking is mainly for the comparison of financial data in the same industry, and intelligent prediction is mainly for the prediction of enterprise profit and enterprise capital structure.

Table 1: Functional analysis of intelligent financial decision support system requirements

Functions	Number of enterprises
Data analysis	14
Smart financial analysis report	10
Industry benchmarking	12
Smart interaction	5
Risk warning	9
Self-service	3
External big data	11
Artificial intelligence modeling	7

Figure 2 shows that the intelligent financial decision support system contains components such as multi-source heterogeneous data layer, application scenarios, and operating decision data sharing platform. The

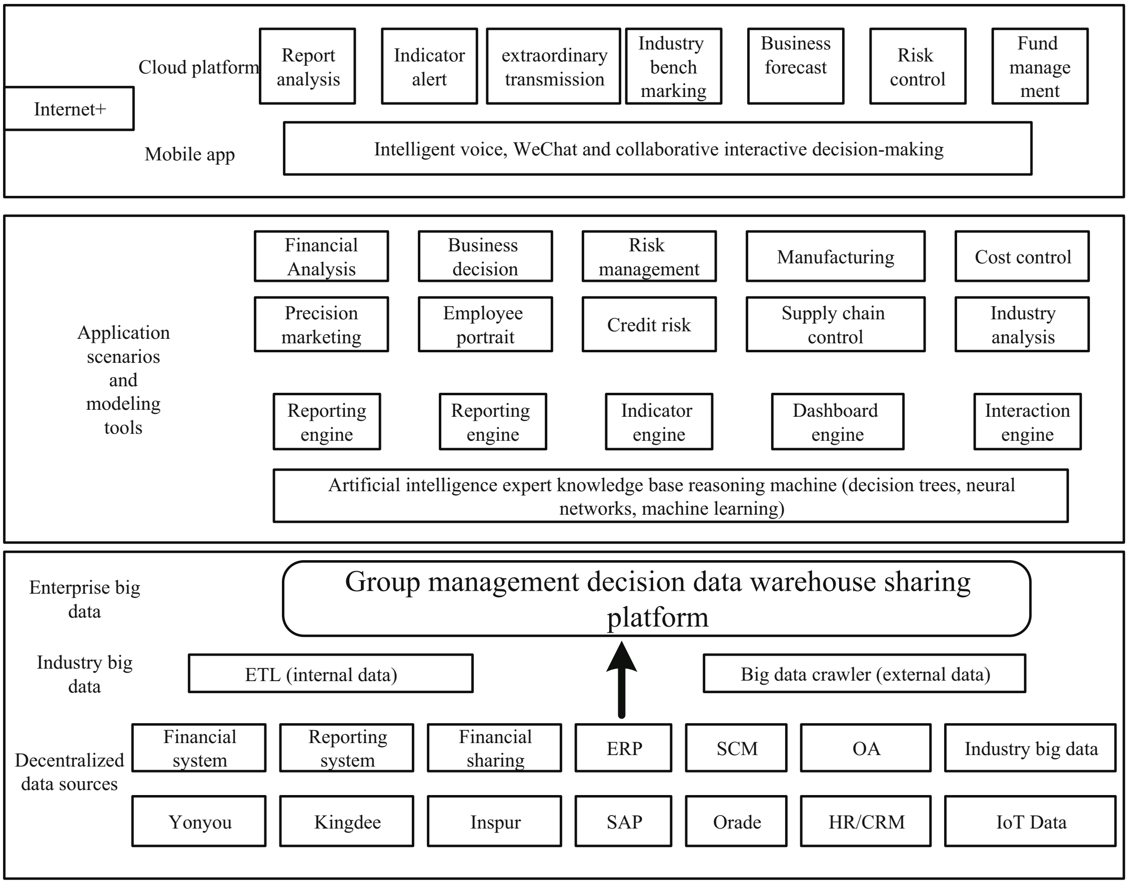

Figure 2: Intelligent financial decision support system architecture.

application scenarios are built by the expert reasoning and financial intelligence support platform, where the modeling tool platform includes the reporting engine, interaction engine, dashboard engine, and indicator engine. Based on the data processing technology to generate financial analysis portal, the human-computer interaction layer is established so that the top management of the enterprise can understand the operation status of their own enterprise in a timely, comprehensive, and accurate manner and help the top management to make decisions.

4 Application effectiveness of intelligent financial decision support system

4.1 The operational effect of intelligent financial decision support system

The experiment takes J Group in S province as an example. After investigation, the problems in J Group's financial management include: first, too many forms, which are not easy to manage. Second, the data are easy to be lost and leaked. Third, the lack of in-depth analysis of financial data. Fourth, some information is entered several times, lacking reference to the same industry data. Fifth, cannot automatically generate charts and text as well as the corresponding enterprise financial management reports. In the architecture of intelligent financial decision support system, the effective mining of external data is realized through big data web crawling technology, and the crawling process is presented through visualization tools, see Figure 3 for details.

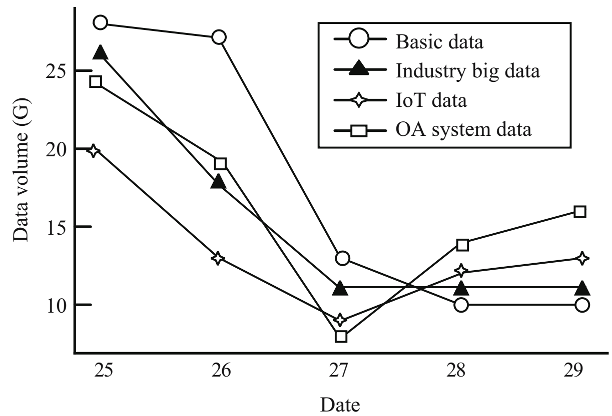

Figure 3: Real-time monitoring of external data.

As shown in Figure 3, with the date as the horizontal coordinate and the data volume as the vertical coordinate, it can be seen that the data collected by the big data web crawler technology are in a state of real-time change. The crawler technology collects and shows the changes in the enterprise finance-related data, including basic data, industry big data, Internet of Things (IOT) data, OA system data, and many other external data, which can supplement the contents of the corresponding enterprise's decision support items and improve the accuracy of decision support.

As shown in Figure 4, multi-dimensional analysis of financial data is completed by OLAP technology. The bar chart is used to display the core indicators of the enterprise such as profits, return on net assets, and accounts receivable. The dashboard is used to display the budget situation of different indicators of the enterprise. Using drill-down to establish the correlation between data and drill-down by company hierarchy, it is convenient for company management to query the status of corporate financial data and conduct linkage queries on the causes of financial variances hidden behind the financial data. Managers can click on the bar chart to view the specific situation of different segments of the enterprise such as operating income, return on net assets, and budget execution rate.

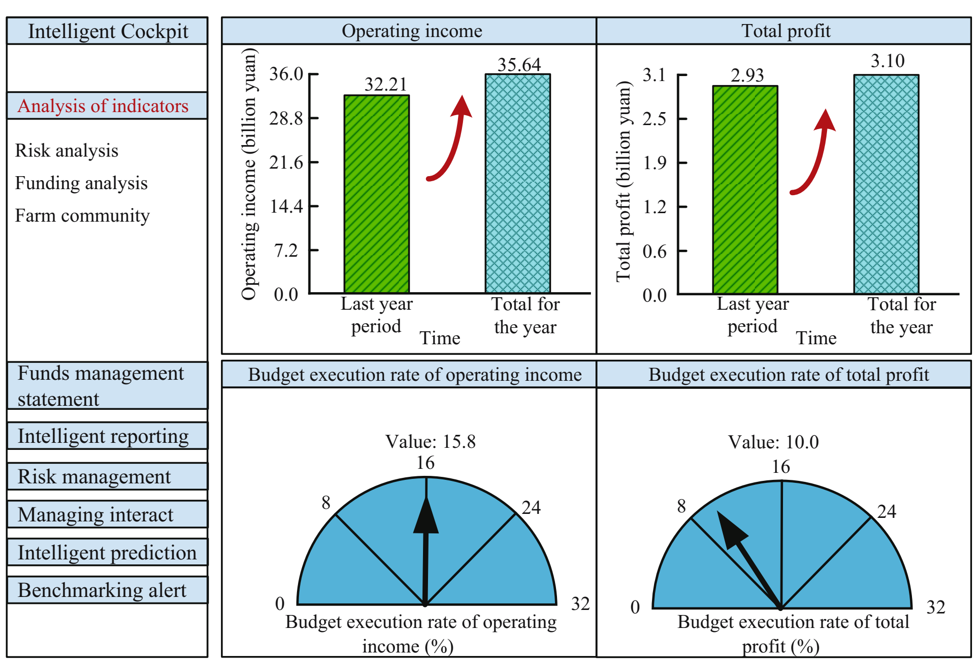

Figure 4: Partial operation results of J Group's intelligent financial decision support system.

As shown in Figure 5, according to the intelligent financial decision support system, J Group's gearing ratio reaches 55.27%, current assets growth rate reaches 10.38%, and operating income growth rate reaches 20.28%. Its financial expenses reach $19.74 million. Its return on total assets is at an excellent level in the industry rating, while the growth rate of total assets is 4.77%, which is at a lower level in the same industry. Overall, its current assets growth is slower than the growth of main business revenue, while the profitability of assets improved and the enterprise's asset structure improves regionally. Managers of this enterprise should make financial decisions with the main purpose of increasing the growth rate of total assets and maintaining the total assets return of the enterprise in a targeted manner.

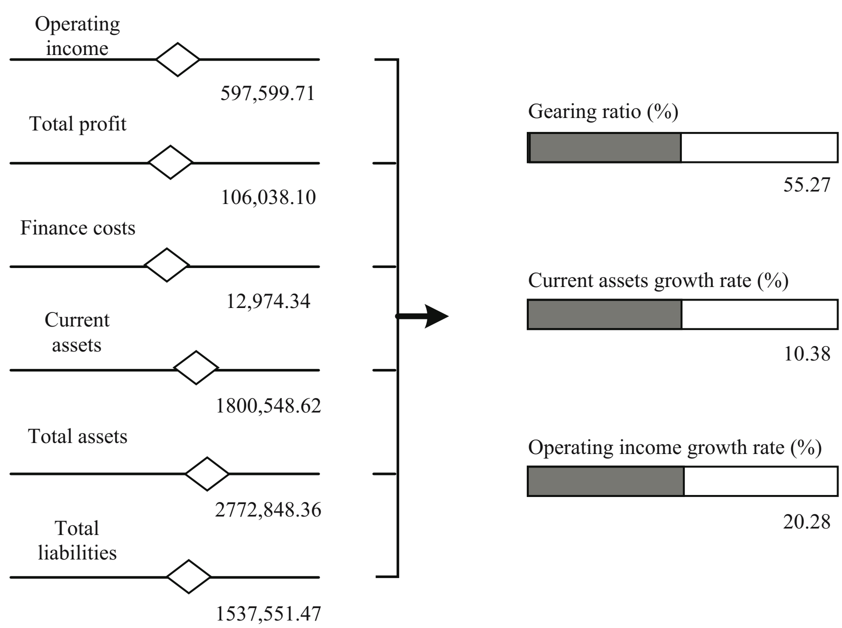

Figure 5: Intelligent prediction results of Group J.

4.2 Discussion of the operational effect

According to the test results of the system operation, the system proposed by the research is far better than the traditional operation mode of the company in terms of data mining capability. The data mining ability of the system proposed by the research institute is mainly realized through crawler technology. According to the test results, the daily mining volume of the system for basic data, industry big data, IoT data, and OA system data reaches 28 G, 26 G, 20 G, and 24 G, which is significantly higher than the traditional data means used by the company. According to the test results, the research institute proposes that the system has user interaction interface and data visualization capabilities. Users can obtain the desired data statistics results through simple operations. These results are displayed in the form of visual charts, enabling users to easily obtain the useful information contained in the data. The data display interface of the system contains multiple core financial indicators. The specific data processing results page can be further expanded by users.

4.3 Application effectiveness of intelligent financial decision support system

By comparing the changes in work efficiency of the group before and after applying the intelligent financial decision support system, the practical application effect of the intelligent financial decision support system designed in this study is analyzed, as shown is Figure 6.

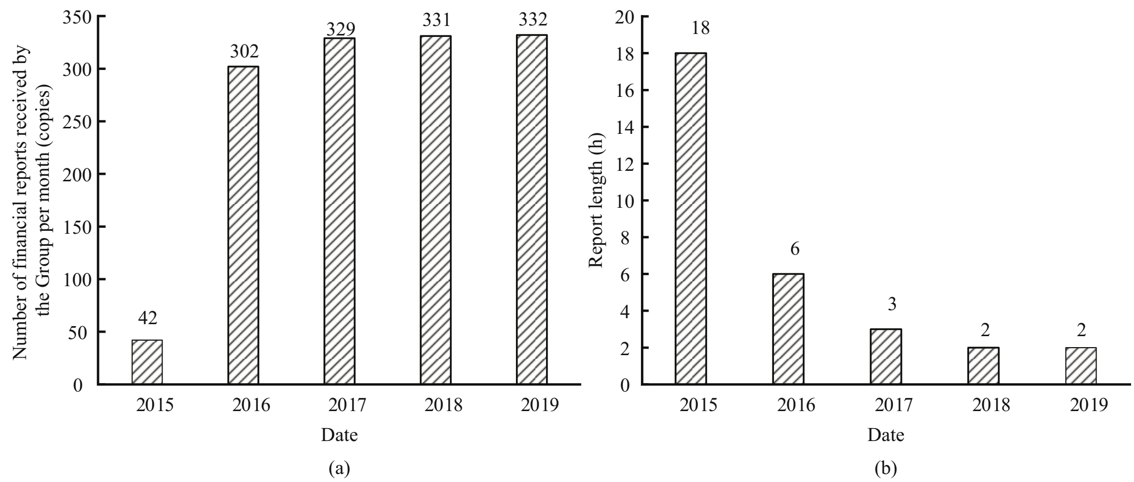

Figure 6: Changes in the efficiency of finance staff before and after the system is on. (a) Number of financial reports received by the Group per month. (b) Monthly time for the Group to complete analysis.

After adopting this intelligent financial decision support system, the number of financial reports received by the enterprise from its subsidiaries per month has increased significantly, and the length of time the enterprise takes to complete the analysis reports per month shows a significant decrease. It indicates that the financial analysis workload of the enterprise is reduced after the application of the intelligent financial decision support system. The application of intelligent financial decision support system also solves the problem of information asymmetry to a certain extent, which is conducive to the group to grasp the financial status of its subsidiaries in a timely manner and improve the control of the enterprise.

From Figure 7(a), it can be seen that this intelligent financial decision support system is applied to the benchmarking analysis of Group J. In terms of sales revenue growth rate analysis, the actual value of Group J is 0.63%, which is 31.27% less than the industry excellent value of 31.90%. The inventory turnover ratio, asset load ratio, and accounts receivable turnover ratio of Group J are lower than the industry excellent value. The interest multiplier earned and return on net assets of Group J are higher than the industry excellent value. Figure 7(b) shows the evaluation results of the profitability of the companies within Group J against the early warning through this system. It can be seen that the return on capital and return on net assets of Group J are at the excellent level, i.e., the return on capital and return on net assets of Group J have reached the level of the excellent value in the industry. Through this intelligent financial decision support system incorporating big data, enterprise managers can technically access relevant data, analyze moving indicators, address existing problems in a timely manner, take effective corrective actions, and ensure the sustainable and healthy development of the enterprise.

4.4 Discussion of the application effectiveness

There may be obvious deviation between the performance of a system in the running test and the actual application. Therefore, after the running test, the system needs to be placed in the actual application environment for testing. According to the changes in the work efficiency of the financial staff after the system went online, the number of financial statements received by the company each month increased significantly. In 2015, the Group received only 42 financial reports per month, and the analysis time of the report was up to 18 h. Since 2016, the number of financial reports received by the Group has exceeded 300, while the time of analysis has been declining. By 2019, the time of analysis has decreased to 2 h. According to the results, the system has significantly increased the amount of data analysis, while the analysis time has decreased, which shows that with the help of the system, the speed and efficiency of the analysts in processing information have increased. From the perspective of data analysis, the experiment then tested the evaluation of the group's profitability

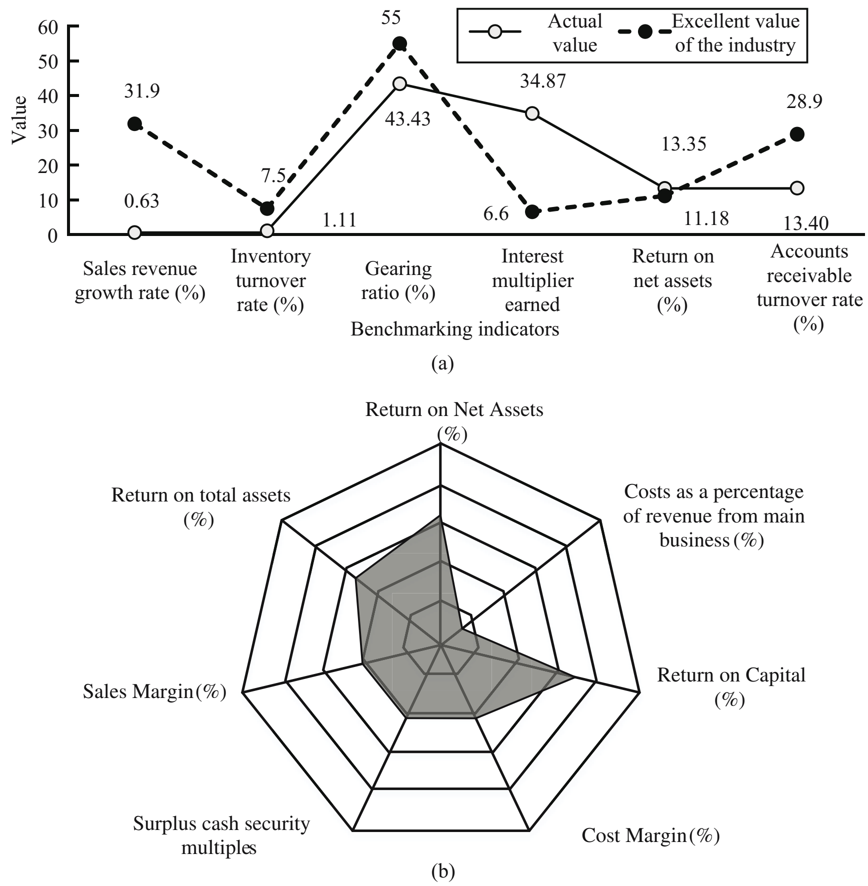

Figure 7: Evaluation of group financial indicators after the system is on. (a) Enterprise benchmarking analysis return on net assets. (b) Industry benchmarking radar chart of corporate profitability.

after the system was launched. The results show that the system can display the financial analysis results of the group in a visual and numerical way, and the analysts can efficiently obtain relevant data and solve problems.

In summary, after the enterprise applies the intelligent financial decision support system designed by the experiment, the enterprise's financial strategy can be better implemented, the enterprise's management is optimized, the enterprise's financial report generation time is shortened and can be generated intelligently, and the usefulness of the enterprise's management decisions are also improved to a certain extent.

5 Conclusion

In the era of big data, low automation of enterprise business data and financial data processing technology needs to be improved. The mining ability of available enterprise financial decision-making information has an important impact on the development speed and stability of enterprises. In order to increase the automation and efficiency of enterprise financial decision support, an intelligent financial decision support system integrating big data is proposed. The system conducts mining and analysis of external and internal data through network big data crawler technology and ETL technology, builds a data warehouse sharing platform for group business decision-making based on the effective data obtained, and uses the cloud computing platform in Internet plus for enterprise report analysis. The analysis content includes indicator warning, abnormal penetration, industry benchmarking, risk control, capital supervision, etc. Combined with the application scenario model, the system can complete the financial analysis, credit risk evaluation, industry analysis, cost control, precision marketing and other management analysis of enterprises. The research results show that big data web crawler technology facilitates real-time monitoring of relevant enterprise data. Enterprise executives can use the intelligent financial decision support system to show the core indicators of the enterprise such as profit, return on net assets, and accounts receivable. Take J Group as an example, after the group applied the intelligent financial decision support system, it can visually analyze the group's asset and liability ratio, current asset growth rate, and operating income growth rate of 55.27, 10.38, and 20.28%, respectively. The number of enterprise's monthly financial reports increased significantly, while the time efficiency of enterprise monthly analysis reports decreased significantly. The actual sales revenue growth rate of the Group was 0.63%, which was less than the excellent value of the industry. The interest earned multiple and return on net assets were higher than the industry's excellent values. The system successfully realizes the real-time interaction of data, and has the characteristics of penetration, linkage, and efficiency, which plays a certain role in promoting the process of big data application management. It also improves the intelligent financial decision support system to a certain extent. The system designed is mainly used for enterprise risk management and control through historical data. Although it has achieved success, it still lacks comprehensive functions. In the future, functions should be expanded to predict and control future risks.

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