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Correlation Analysis of Enterprise Management and Market Economy Decision-Making Based on Absorption of Different Conditions and Driven by Big Data

Na Li[1,*]
[1]School of Economics and Management, University of Science and Technology Beijing, Beijing 100083, China.
Corresponding authors: Na Li (e-mail: lina7643@163.com).

Abstract This paper firstly presents the hierarchical conceptual model and implementation model of the overall framework of the relationship between enterprise management and market economic decision-making based on absorption of different conditions and driven by big data. The overall framework is divided into interaction layer, service composition layer, service layer, business component layer and resource layer. In particular, the service layer includes the basic software components distributed in the enterprise computing environment that can be reused and reorganized and follow standardized interface protocols. Different combinations such as looping, selection, and parallel are used to compile practical solutions. The service component architecture is used to realize the service modeling, the service data object is used as the data and message model, the business process execution language is used to arrange the service, and the enterprise service bus technology based on the system is used to complete the system composition. The experimental results show that the protocol-based hierarchical multi-dimensional data analysis framework in the environment adopts both the aggregation pool object replacement strategy and the real view technology based on the object soft reference technology to improve the query performance of massive multi-dimensional data, to achieve enterprise management and market economy.

Index Terms big data, conditional absorption, enterprise management, association model

I. Introduction

A symbol of the era of intelligence; in my country, in 2015, my country proposed a big data strategy in the "13th Five-Year Plan". In March 2017, the digital economy entered the stage of concrete implementation. In just eight years, the added value of the data economy has been realized. The ability of a company to use and process big data directly determines the level of production and development decisions to a certain extent [1]–[4]. However, at present, most manufacturing enterprises in my country are faced with either being unable to collect useful decision-making data in the commercial field, or unable to realize value conversion in the face of "a mountain of" transaction records and financial information, resulting in increasingly serious data problems. In the event of a disaster, policymakers also mostly resorted to the helpless measure of "too much to deal with" or "to ignore it". According to relevant reports, the proportion of my country's digital economy in GDP has increased year by year, reaching 32.9% in 2017, with a scale of 27.2 trillion yuan. The growth rate is obviously huge but compared with 50% of the developed countries (the United States, Germany, and the United Kingdom), the digital development of Chinese enterprises still has a long way to go [5]. Data information generates information content, and information content improves management decision-making, thus becoming the main force of production [6], [7]. In the future, we can see that data information will become the key to decision-making and assessing the value of companies, as the participants of the 2012 Davos Global Finance Summit in Switzerland declared: the innovation shown by data information is unparalleled [8]. The Audi Group, which realized this early, has a significant core competitiveness, and this article will enable manufacturing companies to deeply understand the necessity of cloud computing technology for the company's manufacturing industry.

For a company, strategic decisions will determine company performance, stronger management decisions may produce stronger organizational performance, and the accumulation of practical effects of excellent management decisions will create the company's core competitiveness. As the basis and foundation of key management decision-making data, may bring new management methods to the company's natural environment, and provide new foundations and methods for companies to discover use value, create wealth and create value, and solve difficulties [9]. In addition, it provides com-

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panies with higher-level training in management and management decision-making [10]. The rapid growth in the scale of data and information operations and the evaluation of the value of the complex linkages between data and information must be made more effectively and directly in companies' strategic decision-making and to find a new business operating model.

In fact, the data foundation of existing enterprise market economic decision-making is mainly based on structured data, while ignoring the importance of unstructured data; the focus is based on the internal financial information and data of the enterprise for analysis and decision-making, while ignoring the external environment of the enterprise, such as macroeconomics environment, national policies, peer competitors and other related information data; focusing on the analysis of historical data, making enterprise market economic decision-making inefficient [11]. Therefore, organically combines big data technology with enterprise market economy decision-making, realizes the integration of relevant data inside and outside the enterprise, and integrates enterprise management and enterprise management based on big data technology method. The effective combination of market economic decision-making has further enriched the research on the theoretical system of enterprise management methods [12].

To sum up, the correlation analysis of enterprise management and market economy decision-making based on the absorption of different conditions and driven by big data is helpful for solving the problems of weak data foundation and lagging decision-making methods in the traditional market economy decision-making process, improving the market competitiveness of enterprises, and realizing the maximum enterprise value [13].

II. Enterprise Management and Market Economy Decision-Making Model

Most of the data used in traditional market economic decision-making is structured data within the enterprise, while big data technology provides new possibilities for the acquisition and storage of data required for enterprise market economic decision-making. The era of big data has brought huge data sources to the financial department of enterprises [14]. Using big data technology, in addition to obtaining internal data of the enterprise, such as financial statement data, it is also possible to obtain data from suppliers, customers, peers through various media such as the Internet and social networks. Enterprises, tax departments, government departments and other parties obtain more data information, including not only structured data, but also more unstructured data, which further consolidates the data foundation. In the past, due to insufficient technical conditions, most unstructured data could not be effectively stored. Its data visualization implementation process is shown in Figure 1.

In this process, financial indicator analysis can generally be divided into two categories, one is report structure analysis, and the other is financial capability analysis. The report structure analysis is mainly based on the data, and studies the company's asset structure [15], liabilities, shareholders' equity structure, etc. By studying the report structure of the enterprise, you can get a preliminary understanding. The financial capability analysis of an enterprise can be mainly analyzed from six aspects: profitability, solvency, operating capability, growth capability, cash flow and capital structure. Profitability reflects the operating results achieved by the company in the current year, debt solvency and capital structure reflect the company's ability to repay debts in the future, operating capability and growth capability reflect the sustainable development capability. Table **??** shows the calculation methods of relevant indicators for enterprise management and market economy decision-making ability analysis.

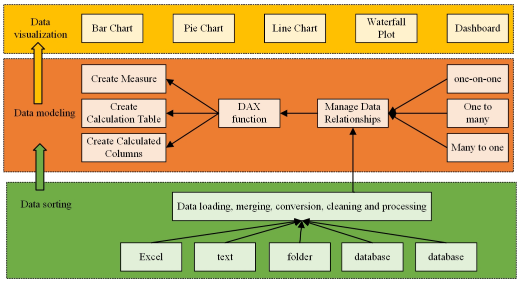

Figure 1: Enterprise management and market economy decision-making model

ability analysis	financial index	Calculation formula
	A	(Profit+interest expense)/total assets
Profitability	B	(Total profit+interest expense)/total net assets
	C	Net profit/total shareholders' equity
	D	Net profit/total shareholders' equity
	E	Net profit Sales revenue
	F	Net profit/total assets
	G	total assets

Table 1: Calculation of relevant indicators for enterprise management and market economy

In the analysis model of enterprise management and market economy decision-making ability, the relevant variables are specifically defined as shown in Table 2.

Based on the above definitions, we can build an analysis model for enterprise management and market economy decision-making capabilities as shown in Eq. (1) to Eq.(4):

$$\begin{aligned}
&\text{Stddroa}_{\text{ i,t}} = \alpha_{10} + \alpha_{11}\text{ Position}_{\text{ i,t}} + \alpha_{12}\text{ Age}_{\text{ i,t}} \\
&+ \alpha_{13}\text{ Growth}_{\text{ i,t}} + \alpha_{14}\text{ Bsize}_{\text{ i,t}} + \alpha_{15}\text{ Sizee}_{\text{ i,t}} \\
&+ \alpha_{16}\text{ Lev}_{\text{ i,t}} + \alpha_{17}\text{ Outratio}_{\text{ i,t}} + \alpha_{18}\text{Cff}_{\text{i,t}} \\
&+ \alpha_{19}\text{ Presmn}_{\text{ i,t}} + \alpha_{110}\text{Tq}_{\text{i,t}} + \alpha_{111}\text{ Top}_{\text{ i,t}} \\
&+ \alpha_{112}\sum\text{Year}_1 + \alpha_{112}\sum\text{Ind}_\text{i} + \varphi.
\end{aligned} \tag{1}$$

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Variable Type	variable	code	Variable meaning
Interpreted variable	Real earnings volatility	STDDROA	The three-year real earnings volatility of an enterprise, that is, the standard deviation of the total return on capital after excluding earnings management factors
Interpretation variable tone	Founder management	position	Measured by dummy variable, the value of management role (chairman, general manager, or both) in private enterprises is 1, otherwise it is 0
Section variable	Founder management Founder Gender Education level of founders	Fage Sex Edu	The logarithm of the founder's actual age If the founder is male, the value is 1; otherwise, it is 0 The final education background of the founder is taken as the measurement standard of education level. The value of master's degree and above is 1, and the value of undergraduate degree and below is 0
control variable	Listing years Growth ability Whether to hold a concurrent post	Age Growth Presmn	1n (1+years of listing) Growth rate of main business income Dummy variable, chairman and general manager are both 1, otherwise 0

Table 2: Definition of variables in the analysis model

$$\begin{aligned}&\text{Stddroa}_{i,t}=\alpha_{20}+\alpha_{21}\text{ Position}_{i,t}+\alpha_{22}\text{ Fage}^{*}\text{ Position}_{i,t}\\&+\alpha_{23}\text{ Fage}_{i,t}+\alpha_{24}\text{ Age}_{i,t}+\alpha_{25}\text{ Growth}_{i,t}+\alpha_{26}\text{ Bsizee}_{i,t}\\&+\alpha_{27}\text{ Size}_{\mathrm{i,t}}+\alpha_{28}\mathrm{Lev}_{\mathrm{i,t}}+\alpha_{29}\text{ Outratio}_{\mathrm{i,t}}+\alpha_{210}\mathrm{Cfo}_{\mathrm{i,t}}\\&+\alpha_{211}\text{ Presmn}_{\mathrm{i,t}}+\alpha_{212}\mathrm{Tq}_{\mathrm{i,t}}+\alpha_{213}\text{ Top}_{\mathrm{i,t}}\\&+\alpha_{214}\sum\mathrm{Year}_1+\alpha_{215}\sum\mathrm{Ind}_1+\varphi.\end{aligned}\tag{2}$$

$$\begin{aligned}&\text{Stddroa}_{i,t}=\alpha_{30}+\alpha_{31}\text{ Position}_{i,t}+\alpha_{32}\text{ Sex}^{*}\text{ Position}_{i,t}\\&+\alpha_{33}\text{ Sex}_{i,t}+\alpha_{34}\text{ Age}_{i,t}+\alpha_{35}\text{ Growth}_{i,t}+\alpha_{36}\text{ Bsize}_{i,t}\\&+\alpha_{37}\text{ Size}_{i,t}+\alpha_{38}Lev_{i,t}+\alpha_{39}\text{ Outratio}_{i,t}+\alpha_{310}\mathrm{Cfo}_{\mathrm{i,t}}\\&+\alpha_{311}\text{ Presmn}_{i,t}+\alpha_{312}\mathrm{Tq}_{\mathrm{i,}t}+\alpha_{313}\mathrm{Top}_{1,t}\\&+\alpha_{314}\sum\mathrm{Year}_1+\alpha_{315}\sum\mathrm{Ind}_1+\varphi.\end{aligned}\tag{3}$$

$$\begin{aligned}&\text{Stddroa}_{i,t}=\alpha_{40}+\alpha_{41}\text{ Position}_{i,t}+\alpha_{42}\text{ Edu}^{*}\text{ Position}_{\mathrm{i,t}}\\&+\alpha_{43}\mathrm{Edu}_{\mathrm{i,t}}+\alpha_{44}\text{ Age}_{\mathrm{i,t}}+\alpha_{45}\text{ Growth}_{\mathrm{i,t}}+\alpha_{46}\text{ Bsize}_{\mathrm{i,t}}\\&+\alpha_{47}\text{ Size}_{\mathrm{i,t}}+\alpha_{48}\text{ Lev}_{\mathrm{i,t}}+\alpha_{49}\text{ Outratio}_{\mathrm{i,t}}+\alpha_{410}\mathrm{Cfo}_{\mathrm{i,t}}\\&+\alpha_{411}\text{ Presmn}_{\mathrm{i,t}}+\alpha_{412}\mathrm{Tq}_{\mathrm{i,t}}+\alpha_{413}\text{ Top}_{\mathrm{i,t}}\\&+\alpha_{414}\sum\mathrm{Year}_1+\alpha_{415}\sum\mathrm{Ind}_{\mathrm{i}}+\varphi.\end{aligned}\tag{4}$$

Where, Sideroad, t represents the real earnings volatility of enterprise i in year t; Position represents founder management; α is the model residual; measures the relationship between founder management and the company's real earnings volatility, if is significantly negative, then Assumption 1 holds, as shown in Figure 2.

The platform provides a good data exchange and data sharing environment, the supply process of production materials, spare parts and general materials in stock is supported by EDI (Electronic Data Interchange), at the same time, the shared platform service platform integrates news and information, logistics and warehousing, transactions And clearing, production and processing delivery, financing intermediary, investment financing, technical consulting and other functions, and connect manufacturing, trade, freight logistics, production and processing service projects, and high commodity circulation costs, is of great significance for reducing the logistics cost of the processing and manufacturing supply chain [16], [17]. Since the introduction of KBP in 2003, all parties have been able to improve their efficient communication and interac-

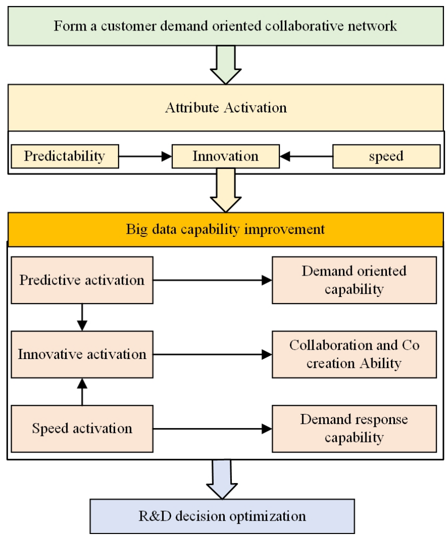

Figure 2: The theoretical model of decision-making optimization

tion capabilities, transparency and optimized processes, and competitiveness. Based on the information sharing platform, the transportation of goods in the procurement process is also particularly critical. DISCOVERY is the abbreviation of digital transportation communication. It is a key element of the digitization of the enterprise transportation process. Freight forwarders and group factories provide all shipping related information. Suppliers use DISCOVERY to issue pickup notices to their respective freight forwarders, and RFID scans are used to track all shipments and returns. The specific process is shown in Figure 3.

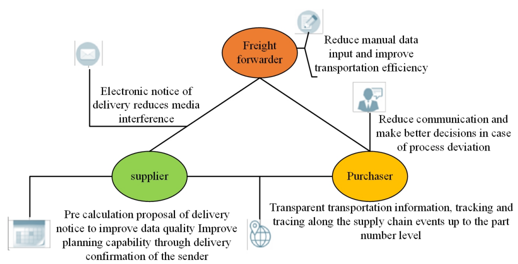

Figure 3: The carrier model of enterprise management

First, use the read_csv function in the panda's third-party library to import the preprocessed data, take the sales revenue

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(store_mone) as the target variable y, and divide the remaining 19 features into the feature vector X [18]. Due to the large data span, data normalization is performed on the target variable and the characteristic variable respectively. The normalization formula used in this paper is Eq.5.

$$X = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})}. \tag{5}$$

After determining the sample data set, perform parameter selection and setting, hyperparameter optimization and other operations, and finally determine the optimal parameter value. Finally, use the optimal parameters for model training to complete the sales prediction model training of L chain enterprises, as shown in Figure 4 and 5.

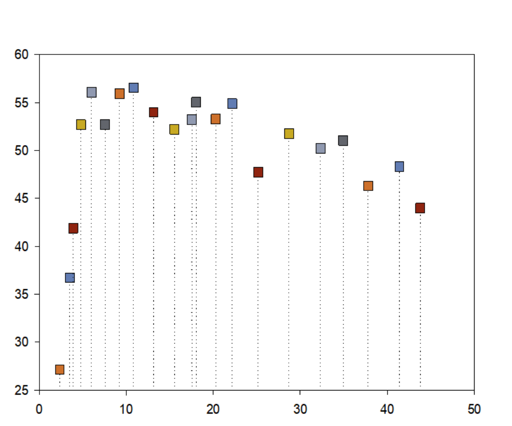

Figure 4: Model Training Set

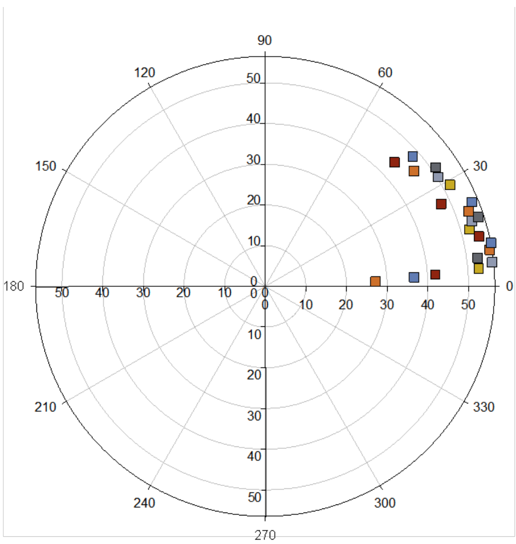

Figure 5: Model Test Set

III. Methods

A. Parameter management and setting

Parameter selection is one of the key steps in the modeling process, including parameters such as booster. The functions and value ranges of each parameter are shown in Table 3.

The boosting model parameters depend on the boosting model used, and different boosting models correspond to different parameters. The function and value range of each parameter are shown in Table 4.

In this paper, when building the XGBoost chain enterprise sales forecast model, the parameter settings are divided into two categories, including general parameters and task parameters. The parameter values are shown in Table 5. Among them, the booster parameter value is set to gbtree, that is, the tree model is used for sales forecasting, the gpu_id parameter is the maximum number of threads in the current system, 8, the objective parameter value is set to reg:squarederror, and the base_score parameter value is 0.5, that is, the initial prediction score is 0.5, the eval_metric parameter value is set to RSME [19]. The adjustment parameters are mainly learning parameters. In this paper, the random search method is mainly used to adjust each learning parameter, and finally determine the appropriate parameter value.

B. Model Construction

The observed variables of exogenous latent variables each have an influence coefficient of ψ on their corresponding exogenous latent variables. By inputting sample data for model fitting, the influence coefficient ϕ, ψ, λ will be obtained [20]. The influence coefficient quantifies the influence of the company management dimension represented by the exogenous latent variables on the market value, as shown in Figure 6.

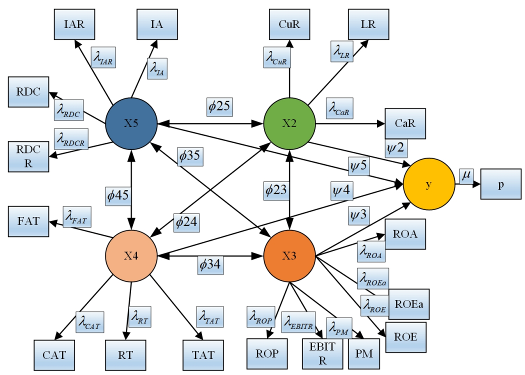

Figure 6: The revised model structure

After the validity analysis in the previous section, the exogenous latent variables were revised, and the exogenous latent variable combinations X2, X3, X4, and X5, which excluded X1, were used as the exogenous latent variable combinations of the model; The observed variables are corrected twice, and some observed variables that make the internal consistency of the observed variable combinations corresponding to the exogenous latent variables are not high. The model after the second revision has the basis of empirical analysis in terms of reliability and correlation. The sample data is derived from

Serial No	parameter	effect	Value range
1	booster	Select Base Learner	The range of values is gbtree, gblinet and dart. The tree model is used as the base learner for gbtree and dart, and the linear model is used as the base learner for gblinear. The default value of the boost parameter is gbtree
2	GPU-id	Control the maximum number of parallel threads	The default is the maximum number of threads available to the current system

Table 3: General model parameter value table of enterprise management

Serial No	parameter	effect	Value range
1	subsample	The proportion of sub samples of the training model in the whole sample set can prevent over fitting	The value range is $(0,1] * 1$, which means that all samples are used when establishing the regression tree, and less than 1 means that some samples are used by not putting back the samples
2	colsample-bytree	The subsampling proportion when building each tree. Subsampling will occur every time a tree is built	The value range is $(0,1]$, and the default value is 1
3	n-estimators	Number of lifting trees, evaluation of the number of iterations of lifting trees	The value range is $(0,-]$

Table 4: Value list of model parameters for enterprise management

Parameter Category	Serial No	parameter	Parameter value
General parameters	1	booster	gbtree
	2	GBU-id	8
Task parameters	3	objective	reg:squarederror
	4	base-score	0.5
	5	eval-metric	rmse

Table 5: Default parameter value table of enterprise management

the 2014 annual report data of the 115-information technology A-share listed companies in the previous section.

IV. Experiments

While the model is running, hyperparameters are parameters whose values are set before starting the learning process. There are many hyperparameters for the XGBoost algorithm. For these hyperparameters in the algorithm that need to be adjusted manually, grid search methods and random search methods can be used for optimization. If the grid search method is used for hyperparameter optimization, each parameter needs to be adjusted separately. If the parameter setting range is wide and there are too many parameters to be optimized, it will not only increase the time cost, and a "dimension disaster" [21], [22]. The random search method can search for the distribution of each hyperparameter in the parameter combination space, add parameter nodes without affecting the performance, and select a better parameter combination, which is much less than the number of parameter combinations under the grid search method of saving time. Therefore, this paper chooses the random search method to optimize the hyperparameters in the XGBoost algorithm, and the hyperparameter optimization is mainly aimed at adjusting the parameters. After specifying the default value parameters of the system, the adjustment parameters in the XGBoost algorithm are optimized by the random search method. The value changes of each parameter during the random search optimization process are shown in Figure 7.

As shown in Table 6, the table that the learning rate parameter value is 0.07, the maximum tree depth is 9, the subsampling ratio is 0.61, the sub-sampling ratio for building trees is 0.71, and the number of trees is 400.

Next, consider the acceptance of the model assumptions of each latent variable in the market value management model.

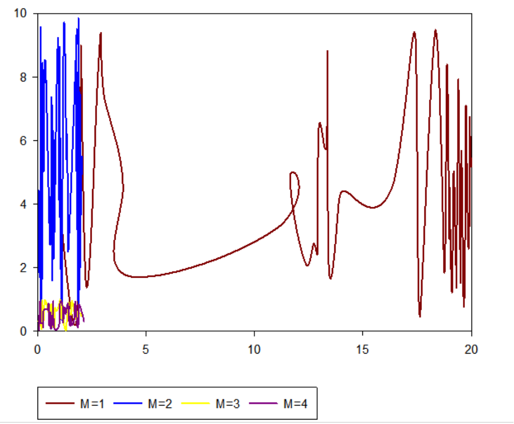

Figure 7: Experimental results of model hyperparameters

Parameter Category	Serial No	parameter	Parameter value
	1	Learning-rate	0.08
Learning parameters	2	Gamma	0
	3	Max-depth	9
	4	Min-child-weight	2
	5	Sub sample	0.62
	6	Colsample-bytree	0.72
	7	n-estimators	401

Table 6: Model random search hyperparameter values

AMOS 21 software provides a statistical significance test p value of the influence coefficient between each latent variable/observed variable, as shown in Table 7.

From the fitting results of the market value management model, the four aspects of large information technology enterprises have different degrees of influence on the market value. The impact of risk tolerance, company business quality, and asset liquidity on the market value of large information technology enterprises is positively correlated, the influence coefficients are 0.158, 0.871, and 0.372, respectively, while the core competitiveness has a weak influence on its market value, and the influence coefficient is only -0.100. For the core competitiveness of large-scale information technology enterprises, Chinese investors have not responded so positively to them. If the enterprise invests a lot of resources in technology research and development and has a certain technical reserve and competition potential [23]. The effect is

Impact path	p value of statistical significance test	Significance
X2 and Y	0.388	Not significant
X3 and Y	0.000	Very significant
X4 and Y	0.041	remarkable
X5 and Y	0.475	Not significant
Cur and X2	-	-
LR and X2	0.000	Very significant
CaR and X2	0.000	Very significant
ROA and X3	-	-
ROEa and X3	0.000	Very significant
ROE and X3	0.000	Very significant
PM and X3	0.096	Not significant
EBITR and X3	0.000	Very significant
ROP and X3	0.000	Very significant
CAT and X4	-	-
RT and X4	0.000	Very significant
TAT and X4	0.000	Very significant
FAT and X4	0.596	Not significant
RDCR and X5	0.759	Not significant
RDC and X5	0.000	Very significant
IAR and X5	-	-
IA and X5	0.000	Very significant
P and Y	-	-

Table 7: Model influence coefficient analysis

not obvious. This shows that in my country's capital market, investors still take financial report data and short-term profits as the main consideration when evaluating the stock price and company value of large information technology companies. In recent years, market competition has been intensifying, and listed companies with improper management or decision-making mistakes may be at a disadvantage in the competition, their performance has been declining, and their stock prices have plummeted, seriously affecting their financing, which will lead such listed companies to conduct financial fraud, to earn more money for yourself. This can also explain the financial frauds of listed companies that inflate their income and profits in an endless stream in recent years to whitewash the company's operations and push up the market value.

V. Conclusion

Informatization not only directly affects the organizational structure change and business process reengineering of enterprises, but also reshapes and integrates the relationship between enterprises and their collaborating partners, the complexity of business continues to rise. As the core decision-making of enterprise management, in today's information age, the decision-making environment is increasingly complex, the decision-making requirements are continuously improved, and the decision-making resources are more abundant many challenges. Business decision makers often need to make quick and effective decisions on emerging issues in a dynamically changing environment. The traditional decision support system revolves around database and model library and consists of various computing components and human-computer interaction components. The coupling between components is strong, and the internal and external interfaces lack standardization. It is a dedicated unit independent of other business systems. The expansion of the traditional decision support system requires the introduction of generators, which not only has a high reconstruction cost, but also has a small adjustment range. The emergence of service-oriented computing technology just solves the problems of closedness and rigidity inherent in the decision support system of traditional market economy.

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