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Research Article

Decision Modeling and Evaluation of Enterprise Digital Transformation Using Data Mining

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The paper discusses the commercial opportunities for digitalization, as well as the changes that occur when digital technology is adopted throughout all business areas. A survey of digital firms found that maturing digital organisations are concentrating on integrating digital technologies to revolutionise how businesses operate. A digital strategy supported by management who nurture a culture of change and innovation is a primary predictor of a company's ability to digitally remake itself. Companies that integrate big data, cloud, mobile, and social technologies into their infrastructure are more lucrative, have larger sales, and have a better market valuation than competitors with a weak vision. This paper aims to conduct an in-depth study on the evaluation and decision-making model of the effectiveness of enterprise transforming to digitalization based on data mining in order to address the shortcomings of self-evaluation, promote and improve the process and promote enterprise transforming to digitalization. First, it determines the evaluation index and uses triangular fuzzy numbers to clarify the index weight. It also gathers the opinions of various experts in the decision-making process. Afterward, the decision tree evaluation model is generated through the information gain and ROC curve. Based on enterprises' relevant transforming to digitalization data, the decision tree model is used as the evaluation decision model, and the research on the evaluation model of the point of enterprise transforming to digitalization is completed. Experiments show that the method proposed in this paper has high accuracy, fast algorithm operation efficiency, and robust data mining ability. It can effectively improve and promote the progress of enterprise transforming to digitalization.

1. Introduction

China's economy has changed from speedy growth to quality development. Implementing new development concepts and building a modern economic system is a need of the hour. There is also a need to reform the enterprise structure, promote the deep integration of advanced technology, improve supply quality, promote optimization, and upgrade China's traditional industries. Some enterprises in China are large-scale and have relatively complete systems. However, there are also problems of being large but not strong. Under the gradual weakening of low-cost advantages of Chinese enterprises, their independent innovation ability becomes poor, and production management efficiency becomes low. Transforming to digitalization is a critical way to improve overall competitiveness. Therefore, it is imperative to speed up the transforming to the digitalization of enterprises.

The weak foundation of transforming to the digitalization of Chinese enterprises and the poor application ability of digital technology are the main reasons for the enormous gaps in the digital capabilities of enterprises. After breaking down barriers between individuals and companies, organisations in the sector are confronting the challenge of adapting to digitalization. They will be able to build innovative services and efficient business practises if these limits are lifted. These changes are occurring in organisations of all sizes. They have one trait: the ability to revolutionise processes and business models, increase worker productivity and creativity, and personalise customer/citizen experiences. To do this, businesses will require an outcome-driven, technology-enabled Digital Business Platform. The use of technology to the creation of new business models, processes, software, and systems results in improved revenue, a stronger competitive advantage, and increased efficiency. Enterprises acknowledge their own needs for transforming to digitalization and choose the most appropriate entry point. Transforming to digitalization is not a single technology application but a proposition of strategy and management. Most enterprises in China do not have an information foundation and talent, so they do not know how to carry out transforming to digitalization or combine their actual situation and needs. They blindly carry out transforming to digitalization. As a result, the digital equipment and software of many enterprises do not meet the needs of enterprises, and transforming to digitalization does not achieve the effect. This paper aims to evaluate the effectiveness of enterprise transforming to digitalization.

The innovations of this paper are as follows: first, it determines the evaluation index of the effectiveness of enterprise transforming to digitalization, uses triangular fuzzy numbers and closeness to clarify the index weight, and gathers various expert opinions in the decision-making process. Then, through the information gain and ROC curve, the decision tree evaluation model is generated. Based on enterprises' relevant transforming to digitalization data, the decision tree model is used as the evaluation decision model of the effectiveness of enterprise transforming to digitalization. Secondly, it compares the other enterprise transforming to digitalization effectiveness and evaluation models. It shows that the proposed method has high accuracy, faster algorithm operation efficiency, strong data mining ability, and can effectively promote enterprise transforming to digitalization progress.

The structure of this research paper is as follows: Section 2 explains the related work done in this study. Section 3 sheds light on the construction of evaluation indicators for the effectiveness of enterprise transforming to digitalization. Similarly, Sections 4 and 5 describe the evaluation and analysis of enterprise transformation effectiveness based on data mining and experimental result. Finally, the concluding remarks are mentioned in Section 6.

2. Related Work

The transformation of an enterprise aims to better adapt to the current environment. With the support of the national government, there is a need to change the business model of the enterprise through existing resources and explore new ways that are most suitable for the survival and development of the enterprise. By taking digital technology as a fusion agent of the digital and experimental economy, the research results show that the speed of enterprise transformation is relatively slow. It is not combined with the current situation of enterprise development. It results in an overall low level of enterprise transforming to digitalization [1]. Digital technology has gradually become a technology that has led the way. In the rapidly changing digital pattern, the transforming to the digitalization of enterprises has aroused widespread concern in society. In the digitalization process, it is essential to scientifically analyze their digitalization level to find a more suitable path for enterprise development and realize the transformation and upgradation of enterprises.

Therefore, based on the detailed analysis of the connotation and essence of digitalization and enterprise digitalization transformation, enterprises must refine specific evaluation indicators and critical process areas using literature research and expert evaluation method and develop a digitalization transformation effectiveness model. The model has five key process areas with 19 first-class and more than 60 second-class indicators. Compared with the current relevant evaluation models at home and abroad, this model can reflect the changes in the enterprise operation mode and digital technology's integration and system application. It also provides researchers with insights into emerging digital phenomena and is conducive to formulating strategic objectives and implementing relevant plans for enterprises [2]. Transforming to digitalization has become the trend of enterprise operation in the era of the digital economy. Traditional enterprises have become data-driven operating enterprises in the process of transforming to digitalization. Against this background, data protection and application are the main aspects of enterprise data resource operation. By establishing an enterprise transforming to digitalization effectiveness evaluation model, focusing on the protection of enterprise data, taking impact evaluation as a guide, referring to the transformation effectiveness theory, and combining with enterprise data management, an enterprise transforming to digitalization effectiveness model includes more than 30 first-class indicators and more than ten second-class indicators can be established. This model is applied to two specific industries in China that provide a basis for the transforming to the digitalization of enterprises; however, no particular method is proposed [3]. The framework structure of the mathematical model is established based on the choice of enterprise transforming to digitalization based on the RCSP model of life cycle theory.

Under this framework, for enterprises with different life cycles, the model transforms the problem of enterprise transforming to digitalization into a decision-making process. It is decomposed into many interrelated and mutually constrained stages. The Delphi technology is used to obtain the evaluation score of the inspection expert group, give the weight calculation method, introduce Bayesian criteria, and clarify the posterior probability from the starting point to the endpoint to obtain the probability matrix. The detailed analysis of the stable distribution of the Markov chain is used to obtain the probability matrix in the case of balance. It also enriches the selection method of evaluation and decision-making but does not put forward specific improvement countermeasures [4].

3. Construction of Evaluation Indicators for the Effectiveness of Enterprise Transforming to Digitalization

In this section of the paper, we will study the establishment of candidate indicators for evaluating the effectiveness of enterprise transforming to digitalization and determination of index weight of enterprise transformation effectiveness evaluation based on the fuzzy analytic hierarchy process. It will help us understand the construction of evaluation indicators for the effectiveness of enterprise transforming to digitalization. The details are as follows.

3.1. Establishment of Candidate Indicators for Evaluating the Effectiveness of Enterprise Transforming to Digitalization. Quantitative indicators shall be selected to evaluate the effectiveness of enterprise transforming to digitalization. Quantitative data can be used to obtain them [5, 6]. The commonly used indicators for evaluating the effectiveness of enterprise transforming to digitalization are obtained through a detailed analysis of more than 70 domestic and foreign documents related to the evaluation of enterprise transforming to digitalization, combined with the characteristics of the evaluation indicators. The specific indicators are shown in Table 1.

Select 12 experts in the field of enterprise transforming to digitalization, send the questionnaire to the experts, and the experts will score the transformation evaluation indicators. When the evaluation index $AV \geq 80\% \times 5 = 4$, it is considered that the expert evaluation results can be adopted; otherwise, it means that this index is eliminated [7, 8]. According to the final score of the candidate indicators, the level of office automation and the proportion of online equipment will be eliminated because of the bandwidth of the backbone network and Internet interface, the application rate of scientific and technological achievements transformation, and the proportion of highly educated talents. The final score of the candidate indicators is shown in Table 2.

After the screening of experts, starting from the three first-class indicators of technological changeability (X), organizational changeability (Y), and management changeability (Z), a total of 26 detailed evaluation indicators are used to establish an enterprise transforming to digitalization effectiveness evaluation model in seven aspects. It includes digital infrastructure, R & amp; D, and digital investment. The specific indicators are shown in Table 3 [9, 10].

3.2. Determination of Index Weight of Enterprise Transformation Effectiveness Evaluation Based on Fuzzy Analytic Hierarchy Process. The weight of the enterprise transforming to digitalization effectiveness evaluation index is measured using the method of fuzzy mathematical theory along with the analytic hierarchy process. It reflects the impact of information fuzziness on the evaluation results [11, 12].

3.2.1. Definition of Triangular Fuzzy Numbers. Note that, $F(R)$ is the fuzzy set of all on R. Suppose $M \in F(R)$, if M membership function is $A(X)$, $R \longrightarrow [0,1]$ is expressed as follows:

$$M(X) = \begin{bmatrix} \dfrac{x-l}{m-l}, & X \in [l,m] \\ \dfrac{x-u}{m-u}, & X \in [m,u] \\ 0, & other \end{bmatrix} \quad (1)$$

In formula (1), $l \leq m \leq n$, l represents the upper bound of the membership function support, u represents the lower bound of the membership function support, and the triangular fuzzy number M is (l,m,u). In the evaluation index model, l represents the most pessimistic evaluation of experts on this index, m represents the most likely evaluation, and u represents the most optimistic evaluation. The function image is shown in Figure 1.

3.2.2. Application of Fuzzy Closeness. Their closeness can measure the degree of closeness between two fuzzy subsets. If an expert's fuzzy average is close, it means that the expert's evaluation structure is closer to the group evaluation results, and the reliability is relatively high. Therefore, the weight is larger [13, 14].

Assuming that A and B are two fuzzy subsets of R, the closeness $\sigma(A,B)$ between them is defined as follows:

$$\sigma(A,B) = \frac{\sum_{x \in U} (A(x) \wedge B(x))}{\sum_{x \in U} (A(x) \vee B(x))} \quad (2)$$

Experts evaluate various indicators according to the evaluation indicators of the effectiveness of enterprise transforming to digitalization. It is assumed that the set of evaluation experts is $D = (D_1, \cdots, D_k, \cdots, D_l)$ Suppose that the evaluation result of each index of k experts D_k is $M = (M_{k1}, \cdots, M_{ki}, \cdots, M_{kn})$, for the ith index, experts make the language evaluation D_k, and the corresponding triangular fuzzy number is M_{ki}. Therefore, the fuzzy closeness between the triangular fuzzy numbers M_{ki} and M_{mi} of experts D_k and D_m is

$$\sigma(M_{ki}, M_{mi}) = \frac{\sum_{x \in U} (M_{ki}(x) \wedge M_{mi}(x))}{\sum_{x \in U} (M_{ki}(x) \vee M_{mi}(x))} \quad (3)$$

Construct the expert evaluation proximity matrix N, in which, for the expert's evaluation results, the proximity is 1.

$$N = \begin{bmatrix} 1 & \sigma(\overline{M}_1, \overline{M}_2) & \cdots & \sigma(\overline{M}_l, \overline{M}_l) \\ \sigma(\overline{M}_1, \overline{M}_2) & 1 & \cdots & \sigma(\overline{M}_2, \overline{M}_l) \\ \vdots & \vdots & \ddots & \vdots \\ \sigma(\overline{M}_1, \overline{M}_l) & \sigma(\overline{M}_2, \overline{M}_l) & \cdots & 1 \end{bmatrix} \quad (4)$$

The closeness of the average expert D_k is defined as the k-th row of the matrix N divided by $\sigma(\overline{M}_k, \overline{M}_k) = 1$, the average value of other elements is

$$\sigma_{D_k} = \frac{1}{l-1} \sum_{j=1, j \neq k}^{l} \sigma(\overline{M}_j, \overline{M}_k) \quad (5)$$

Table 1: Evaluation indicators for the effectiveness of enterprise transforming to digitalization.

Secondary indicators	Tertiary indicators	Secondary indicators	Tertiary indicators
Digital infrastructure construction capacity	Intranet access rate	Organizational structure transformation ability	Digital sector leadership
	Internet access rate		Number of enterprise management levels
Digital R & D capability	Backbone and internet interface bandwidth	Digital talent construction ability power	Proportion of digital talents
	Application rate of data security measures		Digital skilled employee coverage
	Output rate of new products		Expenditure ratio of digital skilled talents training
	Transformation and application rate of scientific and technological achievements		Proportion of highly educated talents
Digital input capacity	R&d input intensity	Business digital management capability	E-commerce application ratio
	Number of patents application success rate		Office automation level
	Proportion of digital investment		Service response time ratio
	Proportion of digital equipment investment		Order on time delivery rate
	Proportion of digital operation and maintenance		Data visualization rate
Financial digital management ability	Proportion of data security investment	Production digital management capability	Proportion of online equipment
	ERP system coverage		Automation rate of production equipment
	Capital turnover rate		Proportion of digital equipment directly connected to production software
	Inventory capital turnover rate		Product defect detection rate
			Comprehensive utilization rate of equipment

Table 2: Final scores of candidate indicators.

Tertiary indicators	Final score	Tertiary indicators	Final score
Intranet access rate	4.18	Digital sector leadership	4.43
Intranet access rate	4.08	Number of enterprise management levels	4.38
Backbone and internet interface bandwidth	3.65	Proportion of digital talents	4.58
Application rate of data security measures	4.23	Digital skilled employee coverage	4.25
Output rate of new products	5.00	Expenditure ratio of digital skilled talents training	4.42
Transformation and application rate of scientific and technological achievements	3.45	Proportion of highly educated talents	3.38
R&D input intensity	4.54	E-commerce application ratio	5.00
Number of patents application success rate	4.65	Office automation level	2.93
Proportion of digital investment	5.00	Service response time ratio	4.68
Proportion of digital equipment investment	4.58	Order on time delivery rate	5.00
Proportion of digital operation and maintenance	4.38	Data visualization rate	4.46
Proportion of data security investment	4.62	Proportion of online equipment	2.50
ERP system coverage	4.88	Automation rate of production equipment	4.53
Capital turnover rate	4.38	Proportion of digital equipment directly connected to production software	4.43
Inventory capital turnover rate	4.28	Product defect detection rate	5.00
		Comprehensive utilization rate of equipment	4.48

Table 3: Enterprise transforming to digitalization effectiveness evaluation index system.

Secondary indicators	Tertiary indicators	Secondary indicators	Tertiary indicators
Digital infrastructure construction capacity x1	Intranet access rate x11	Organizational structure transformation capability Y1	Digital sector leadership Y11
	Intranet access rate x12		Number of enterprise management levels Y12
	Application rate of data security measures x12	Digital talent construction capability Y2	Proportion of digital talents Y21
Digital R & D capability x2	Output rate of new products x21		Digital skilled employee coverage Y22
	Transformation and application rate of scientific and technological achievements x22		Expenditure ratio of digital skilled talents training Y23
	R&d input intensity x23	Business digital management capability Z1	E-commerce application ratio Z11
Digital input capacity x3	Number of patents application success rate x31		Service response time Z12
	Proportion of digital investment x32		Order on time delivery rate Z13
	Proportion of digital operation and maintenance x33		Data visualization rate
	Proportion of data security investment x34	Production digital management capability Z2	Automation rate of production equipment Z21
Financial digital management ability Z3	ERP system coverage Z31		Proportion of digital equipment directly connected to production software Z22
	Capital turnover rate Z32		Product defect detection rate Z23
	Inventory capital turnover rate Z33		Comprehensive utilization rate of equipment Z24

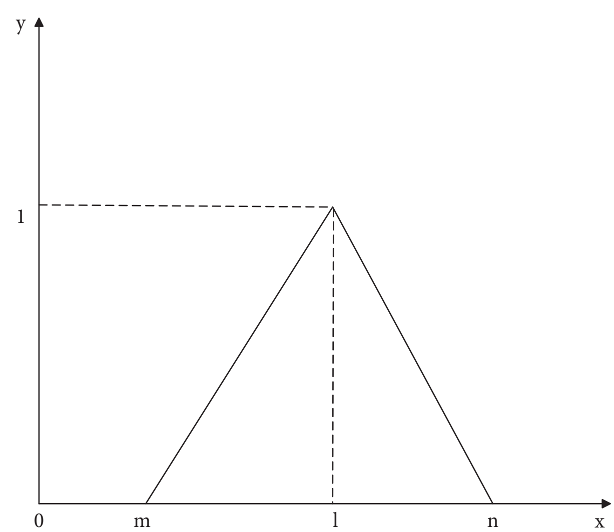

Figure 1: Membership function diagram of triangular fuzzy numbers.

Figure 2 shows the calculation process of index weight based on the triangular fuzzy number analytic hierarchy process.

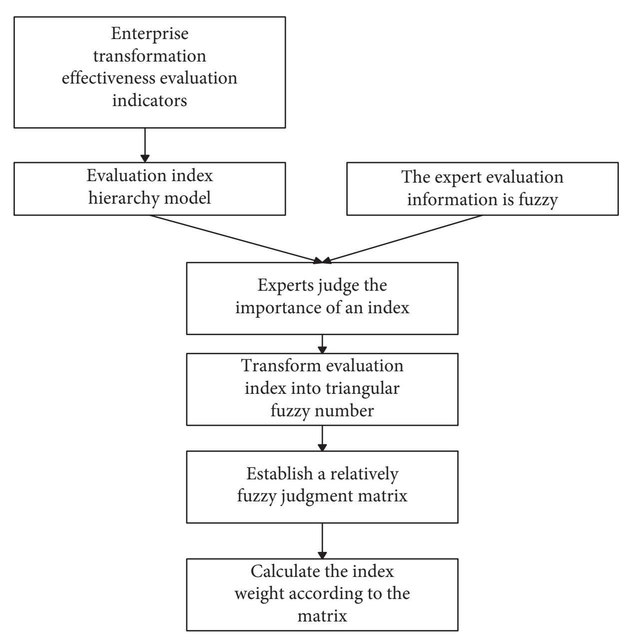

Figure 2: The calculation process of index weight based on triangular fuzzy number analytic hierarchy process.

4. Evaluation and Analysis of Enterprise Transformation Effectiveness Based on Data Mining

This section explains the information gains, evaluation of the decision tree model, ROC curve, and decision tree model. These elements will help evaluate and analyze enterprise transformation effectiveness based on data mining. The explanation is as follows.

4.1. Information Gain. Information entropy represents the information gain of uncertainty. It can measure the impact of a feature on the classification results of enterprise transformation effectiveness [15, 16].

Information entropy is expressed as follows:

$$Info(D) = -\sum_{i=1}^{c} p_i \log(p_i) Info(D) \tag{6}$$

Formula (6), D represents the training data set, c represents the number of categories of enterprise transforming to digitalization data, and p_i represents the proportion of the number of category i samples to the total number of samples.

For the corresponding data set D, when the feature A is selected as the judgment node of the decision tree, the information entropy after the action of the feature A is $Info(D)$, and the calculation is expressed as follows:

$$Info_A(D) = -\sum_{i=1}^{k} p_i \frac{|D_j|}{|D|} \times Info(D_j) \tag{7}$$

Formula (7), k represents the value of information entropy reduction of enterprise transformation data sample D after the action of feature A, which can be expressed as follows:

$$Gain(A) = Info(D) - Info_A(D_j) \tag{8}$$

Compared with the feature selection suitable for the decision tree nodes, it is the feature with the largest $Gain(A)$ value.

4.2. Evaluation of Decision Tree Model. Create a decision tree model and test it with a check set. Classification accuracy, recall rate, false alarm rate, and accuracy are among the evaluation indicators. These are computed using the confusion matrix [17, 18].

This paper primarily studies the significance of the effects of enterprise transforming to digitalization. The confusion matrix mainly evaluates the accuracy of the supervised learning model. Each column of the matrix represents the prediction of a category example. Therefore, the class with a significant impact on enterprise transforming to digitalization is regarded as 1, and the class without significant effect is 0. These are presented in Table 4.

In Table 4, P signifies the number of positive cases of enterprise transformation effectiveness, N denotes the number of negative cases of enterprise transformation effectiveness, TP signifies the number of positive cases correctly predicted, EP represents the number of negative cases indicated into positive cases, FN represents the number of positive cases predicted into negative points, and TP and TN characterize the number of negative cases correctly projected.

Various indicators obtained from Table 4 are as follows.

The classification accuracy probability is expressed as follows:

$$Accuracy = \frac{TP + TN}{P + N} \tag{9}$$

The recall rate is expressed as follows:

$$Recall = \frac{TP}{P} \tag{10}$$

The false alarm rate is expressed as follows:

$$Fprate = \frac{FP}{N} \tag{11}$$

The accuracy is expressed as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{12}$$

The positive example coverage is expressed as follows:

$$Sensitivity = \frac{TP}{TP + FN} \tag{13}$$

Negative case coverage is expressed as follows:

$$Specifcity = \frac{TN}{TN + FP} \tag{14}$$

4.3. ROC Curve. The ROC curve is drawn by using two index values. Among them, the X axis represents specificity, which is the negative case misjudgment rate, and the Y axis represents sensitivity, which is the positive case coverage rate. It is shown in Figure 3.

4.4. Decision Tree Model. It can be seen from Figure 3 that the area AUC under the ROC curve is 0.87, which exceeds 0.8. It is considered that the effect of model fitting is suitable, and the decision tree is visually displayed [19-20]. By pre-pruning the decision tree, the node splitting of the decision tree is based on the gain principle of maximum information entropy. In each node, if the information entropy is greater, the purity of the sample distribution in the node will be lower, and the amount of information that can be provided will be less. The generated decision tree is shown in Figure 4.

The data construction and application ability in Figure 4 is an important indicator to evaluate the effectiveness of enterprise transforming to digitalization. Therefore, through variables as the root node, build a decision tree to classify the enterprises and draw the characteristics of different enterprises. The above-given process completes the research on the evaluation model of the effectiveness of enterprise transforming to digitalization based on data mining.

5. Experimental Result

Take the accuracy of enterprise transformation data classification, data mining ability, and algorithm operation efficiency as verification indicators. To validate the effectiveness of the enterprise transforming to a digitalization evaluation and decision-making model, simulation experiments are carried out. Figure 5 shows the comparison of data classification accuracy between the decision tree

Table 4: Confusion matrix.

Actual class	Remarkable achievements in transforming to digitalization = 1	Remarkable achievements in transforming to digitalization = 0
Remarkable achievements in transforming to digitalization = 1	TP	FN
Remarkable achievements in transforming to digitalization = 0	FP	TN
	P	*N*

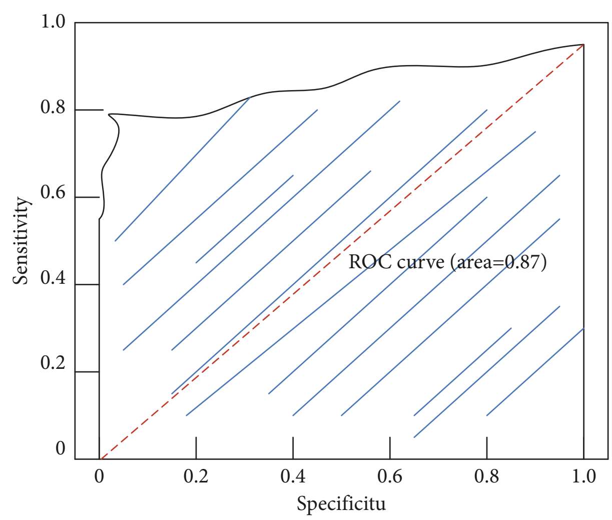

Figure 3: ROC curve of decision tree.

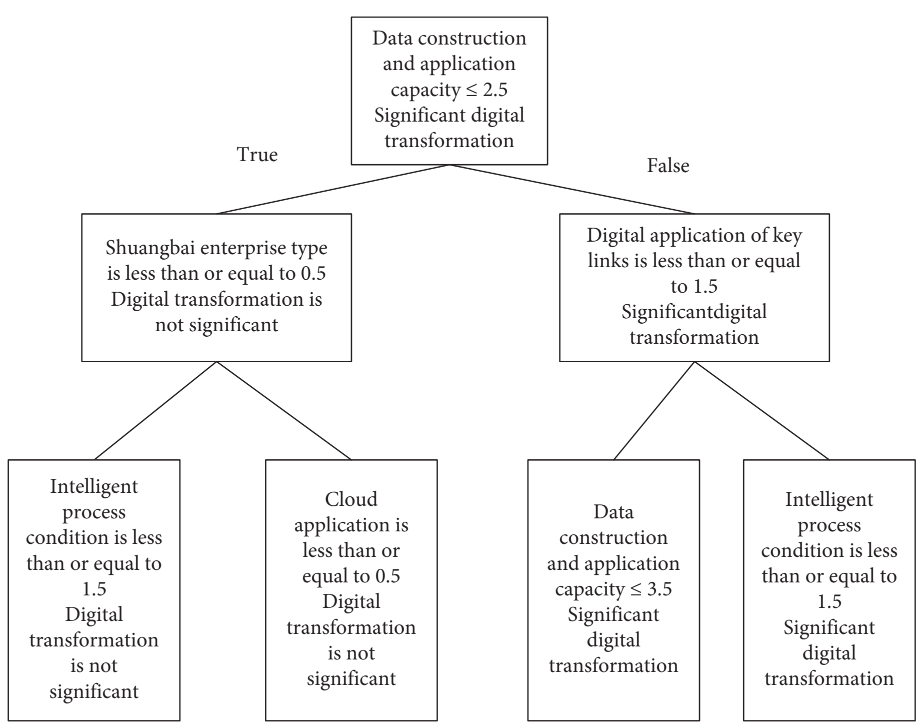

Figure 4: Visualization of decision tree.

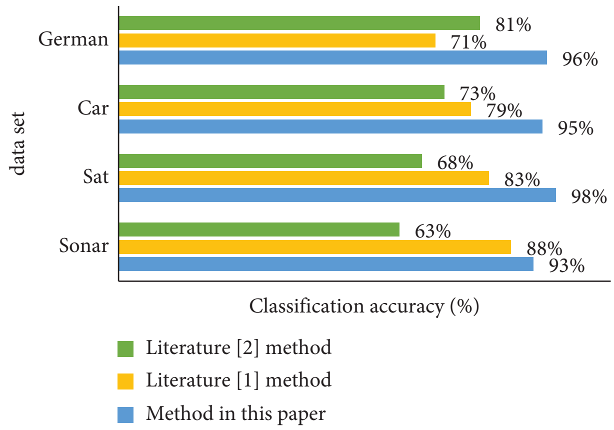

Figure 5: Comparison of data classification accuracy of different methods on different data sets.

analysis method proposed in this paper and the methods presented in the literature [1, 2].

By analyzing Figure 5, we can see differences in the classification accuracy of enterprise transforming to digitalization data using different methods on data sets. The highest accuracy of data classification using the method proposed in the literature [1] on each data set is the sonar data set, with a classification accuracy of 88%. The data set with higher accuracy of data classification using the method proposed in the literature [2] is the German data set, with a classification accuracy of 81%, The classification accuracy of the proposed method on each data set is more than 90%, and the highest data set is sat, with the classification accuracy upto 98%. Table 5 compares the operational efficiency of the approach described in this work to the literature [1, 2]. It illustrates that the technology suggested in this study can categorise corporate transforming to digitalization data properly and increase transformation impact.

Figures 6 and 7 show the comparison of enterprise data mining capabilities using the methods proposed in this paper and traditional techniques. It demonstrates that the strategy described in this study has a good operational effect and may effectively increase data mining efficiency in corporate transforming to digitalization. It can be seen from Table 5 that, compared with the methods presented in the literature [1, 2], the operation efficiency of this method is the highest. At the same time, as the number of enterprise data samples increases gradually, the operation efficiency of the process proposed in this paper shows a slow upward trend, whereas as the number of enterprise data samples increases gradually, the efficiency of algorithm operation also gradually declines, with no upward trend.

Figures 6 and 7 in this paper show the proposed method's data mining ability. Figure 6 shows that the ability to mine enterprise data using the proposed method in this paper is relatively strong. The accuracy of data mining using the method proposed in this paper is relatively high from the start of the experiment. The accuracy of data mining has not changed much with the gradual increase in data volume, and the fluctuation is minor. As shown in Figure 7, the accuracy of data mining has been maintained at more than 85%; the

Table 5: Comparison of operation efficiency of different algorithms.

Number of data samples(Piece)	Method in this paper (%)	Literature [1] Method/5	Literature [2] method (%)
300	72	68	61
600	75	67	58
900	76	68	56
1200	78	62	52
1500	79	60	50

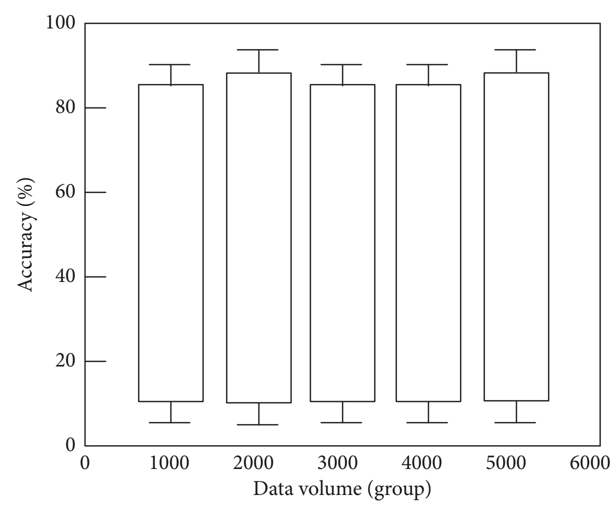

Figure 6: Data mining capability of the method proposed in this paper.

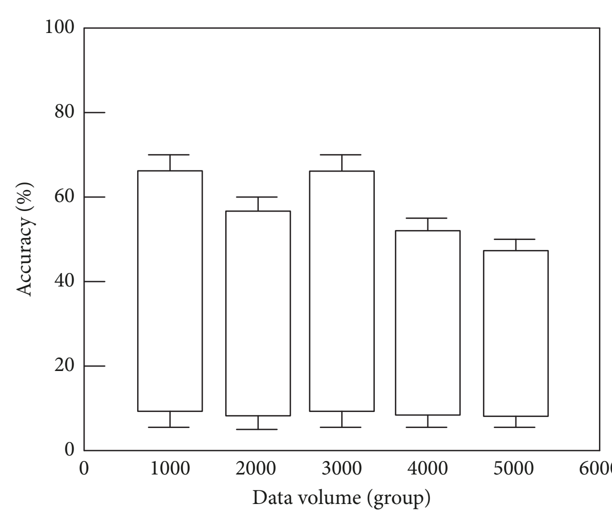

Figure 7: Data mining ability of traditional methods.

ability of data mining using traditional approaches is inadequate. From the start of the trial, data mining accuracy is lower than the approach provided in this work. As the amount of data rises progressively, the accuracy of data mining swings drastically. When the amount of data reaches

5000, the accuracy of data mining is at its lowest. It demonstrates that the method proposed in this paper can effectively mine data with an increasing amount of information to improve the effect of enterprise transforming to digitalization.

6. Conclusion

Today's businesses desire a favourable business climate that does not impede their potential to innovate. In today's global business environment, a company's ability to quickly and effectively adapt to changes is a vital success factor. The basic determination of transforming to digitalization is to enable organisations to adapt to rapidly changing business environments. Its implementation requires a well-defined strategy and prioritisation, as well as financial resources, leadership, and active participation from all personnel inside the organisation. The flow speed is determined by the sector. The present tendency is for fast growth of global connection. Cloud computing, big data and analytics, mobility and Internet access, e-commerce, social media, intelligent sensors, and the Internet of Things are all transforming the global economy. Four converging forces are producing critical technologies that will have a substantial influence on the corporate industry in the next years: social networks, mobile devices, cloud computing, and data analytics. In and of itself, these forces are unique and innovative, but when combined, they radically transform business and society, breaking old business models and ushering in new leaders. These factors together opened the door for transforming to digitalization platforms. As a result, this article investigates the success of business transforming to digitalization in depth. To analyze transforming to digitalization assessment indicators, the decision tree technique is utilised. Experiments have shown that the suggested strategy in this research may successfully enhance corporate transforming to digitalization and increase the efficacy of transforming to digitalization.

Data Availability

The data used to support the study are available on reasonable request from the corresponding author.

Conflicts of Interest

The author declares there are no conflicts of interest in publishing this paper.

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