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Article

A strategy optimization method for technology companies combining SWOT matrix model and decision tree analysis

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Abstract: In the face of the complex and severe international situation and heavy development and reform tasks, it is urgent to establish an efficient organization system of strategic scientific and technological forces, and give full play to the key role of scientific and technological enterprises in the system of strategic scientific and technological forces. In order to enhance the strategic optimization and selection ability of science and technology enterprises, this paper establishes the strategic decision-making index system of science and technology enterprises and uses principal component analysis to obtain its common factors and index weights. Then we take Y Science and Technology Company as the research object, analyze the influence of its internal and external environment by combining the SWOT matrix model, and input the strategic decision indicators into the decision tree model to predict the strategic optimization choice ability of science and technology enterprises. It is found that the decision tree model's prediction accuracy is up to 76.04%, which is 13.89% higher than the logistic regression model's accuracy in the whole model. The decision tree model can provide multiple feasible paths for the strategic optimization choice of science and technology enterprises, and the enterprises can make reasonable choices according to their own situation, thus enhancing the science and technology enterprises to gain a foothold in the increasingly fierce market.

Keywords: technology enterprises; strategy optimization; principal component analysis; SWOT matrix model; decision tree model

1. Introduction

From the 1960s, the term strategic management of business was gradually understood. In the 1970s, Chandler proposed the environment-strategy-organization theory through continuous research. By the 1980s and 1990s, Porter, Prahalad, and Hopland proposed the competitive strategy theory, the core competence theory, and the strategic alliance theory, respectively, after in-depth research [1-3]. With the continuous improvement of Internet technology, the pattern of each industry has been adjusted, the strategic thinking of enterprises has changed greatly, and enterprises have proposed platform strategy, structured innovation strategy and so on in the actual development [4-5]. Based on the strategic management theory proposed by Michael Porter for in-depth exploration, followed by the summary of the theory of competitive strategy, he said that enterprises need to combine their own development status quo and needs to choose the appropriate competitive strategy, and the competitive strategy mainly consists of three types, respectively, cost leadership strategy, differentiation strategy, centralization strategy [6-8].

Cost leadership strategy means that the enterprise strengthens its own cost control ability during the production period, and controls the total cost of inputs during the production period below the competitors, so as to realize the lowest cost in the whole industry [9]. Simplify the product design, develop more efficient production techniques by incorporating innovativeness, focusing on material savings, and reducing capital investment in labor.

The strategy of differentiation means that the enterprise should produce personalized products, which requires the enterprise needs to deeply understand the real needs of customers, and incorporate the elements that customers consider valuable into the product, so that it can make its own products and the competition's products have obvious differences [10-11]. If the enterprise wants to adopt this strategy must test itself to meet the following three conditions [12]. First, the enterprise's high level of innovation and research and development, the current product quality and production technology can be recognized by the industry and has a certain degree of influence. Second, the enterprise's marketing level is high, can explore the potential needs of the market and maintain the synergy between product development and the market. Third, the enterprise will proactively attract professional talents. By adopting this strategy, it can effectively increase customer loyalty to the company and thus take more initiative in commodity pricing.

Concentration strategy means that the enterprise needs to determine the target market, or segmentation based on the current market, and then precisely push the business activities to the segmented market and the corresponding area, so the strategy is also known as focus strategy [13]. This strategy is divided into four main types, which are customer, region, product line, and low market share concentration strategy. Concentration strategy can satisfy the needs of different consumers and give them different ways to use the product [14]. Due to the limitation of internal resources, which makes the size of the market segments is not large, different segments of the market bring different economic benefits to the enterprise, and there will be differences in the rate of economic growth [15]. Through the centralization strategy, the centralized application of enterprise resources, so that enterprises can have a full investigation of product-related technology, market and customer aspects of the situation, the strategic objectives of the centralized and easy to measure the results of the strategic management is easy to control [16].

SWOT model is a commonly used strategic analysis method, which was proposed in the early 1980s by Weirick, a professor of management at the University of San Francisco in the United States, and is often used in corporate strategy formulation, competitor analysis and other occasions [17-18]. SWOT analysis is a kind of comprehensive analysis of the advantages and disadvantages existing in the internal environment of the enterprise, as well as the opportunities and threats existing in the external environment of the enterprise, and according to the results of the analysis to choose the best strategy to prevent the method [19]. Since then, SWOT analysis has been widely used in various fields, and most researchers believe that SWOT analysis is a “powerful tool” for continuous improvement and optimization of decision-making [20].

Information technology, as the core force to promote global industrial restructuring and enterprise strategic transformation, is profoundly affecting the evolution path of enterprise strategic management, and data visualization tools and intelligent prediction systems should be developed to provide real-time basis for strategic adjustment, performance assessment and risk early warning [21-23]. Decision tree is a machine learning method built on the basis of information theory. It is the use of charts and graphs to express a variety of alternatives, and each program or event may lead to two or more events, leading to different results, due to the analysis of a variety of options for decision-making points of the various connecting lines shaped like a tree that falls down horizontally, so it is called decision tree analysis [24-25]. The basic idea is to build a decision tree from a batch of known training data, and then use the built decision tree to predict the data [26]. It can clearly and intuitively represent the various elements affecting the decision, and determine the course of action for solving the problem by judging the probability of the occurrence of various scenarios and the final expected value [27]. Decision tree mainly includes four features [28-30]: first, it facilitates sequential, step-by-step, intuitive and thoughtful consideration of problems. Second, it can visualize the decision-making process of the whole decision problem at different stages in time and decision sequence. Third, when applied to complex multi-stage decision-making, the stages are obvious and the levels are clear, which facilitates collective research and correct decision-making by decision-making organizations. Fourth, it is easy to deal with the decision-making of complex problems.

The technology enterprise strategy optimization method that combines the SWOT matrix model with decision tree analysis takes advantage of the SWOT model to generate key, decision-requiring strategic options, potential risks and opportunity events. These options are then evaluated through a decision tree, thus elevating the strategic discussion from theoretical analysis to data simulation and helping decision makers make more scientific and robust strategic choices.

In order to improve the strategic choice decision-making ability of science and technology enterprises, the article proposes a modeling method based on decision tree and SWOT matrix model. The method utilizes principal component analysis to streamline and design the weights of strategic decision-making indicators of science and technology enterprises, and introduces the SWOT matrix model to analyze the influence of environmental factors in which science and technology enterprises are located. Then, based on the public factors obtained from principal components, it is input into the decision tree model to realize the prediction of the strategic optimization choice of science and technology enterprises. The study shows that the feasibility of the method in this paper is high, and it can generate multiple strategic optimization paths for science and technology enterprises, and the feasibility of the paths is also clearly differentiated, so that science and technology enterprises can make reasonable choices according to their own strategic decision-making situation.

2. Modeling strategic decision-making in science and technology enterprises

Strategic model innovation is an important way for enterprises to find potential business opportunities, change the mechanism of value creation and value capture, gain competitive advantages, and realize rapid growth in an uncertain environment. Science and technology enterprises are a large and special group, playing an important role in the implementation of the national innovation-driven development strategy, and of special significance to the social and economic development and national economic security. In the face of the impact and challenges brought about by the constant emergence of new enterprises, new business forms and new business models in the new context, how to carry out effective strategic model innovation has become an important issue for science and technology enterprises to be solved.

2.1. Indicators for strategic decision-making in science and technology enterprises

2.1.1. Strategic decision-making indicator system design

In order to achieve sustainable development in the new situation, science and technology enterprises need to have a new development strategy, key objectives and central work, according to which a new performance evaluation index system is needed to promote the realization of the objectives and tasks. For science and technology enterprises, it is necessary to create a new business model to achieve strategic optimization, while the new strategic optimization needs to optimize the original performance indicator system of the enterprise, so as to improve the strategic performance system and promote the strategy of science and technology enterprises. Based on summarizing the current research, this paper aims to establish a strategic decision-making indicator system belonging to science and technology enterprises, the specific content of which is shown in Table 1. When optimizing the strategic deployment of science and technology enterprises, it is necessary to comprehensively consider the achievement of strategic decision-making indicators in order to better promote the optimization of corporate strategic decision-making.

Table 1. Strategic decision-making indicator system.

First index	Second index	Code
Profited ability	Eva indicator	PA1
	Receivable turnover	PA2
	Inventory turnover	PA3
Operational efficiency	Total asset turnover	OE1
	Strategic plan completion rate	OE2
	Turnover of current assets	OE3
Institutional construction	Project management	IC1
	Integrated management	IC2
	Customer sentiment system construction completion rate	IC3
Customer management	Customer satisfaction	CM1
	R&D schedule and planning compliance	CM2
	New product customer growth	CM3
Talent cultivation	Research and development team job satisfaction rate	TC1
	The position is adjusted for the adjustment	TC2
	Key position talent satisfaction rate	TC3
	Innovation results increase	TC4

2.1.2. Determination of weights by principal component analysis

Principal Component Analysis (PCA) describes the changes in the data by linearly transforming the original data into a set of uncorrelated principal components by transforming multiple correlated variables into a set of uncorrelated principal components, so that a smaller number of significant variables can be selected to describe the changes in the data [31]. The calculation steps of principal component analysis are as follows:

(1) Assume that the matrix of n observations of the original variables $X_1, X_2, \ldots, X_m$ is:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} = \left(X_1, X_2, \ldots, X_m\right) \tag{1}$$

(2) The data matrix is normalized serially and the normalized data matrix is still noted as X . Zero mean normalization (z-score normalization) was used in this study.Z-Score normalization is a common method of data processing, by which data of different magnitudes can be transformed into Z-Score scores of the same measure for comparison. It improves data comparability and weakens data interpretability. The formula is as follows:

$$x^* = \frac{x - \overline{x}}{\sigma} \tag{2}$$

where $\overline{x}$ is the mean of the original data and σ is the standard deviation of the original data.

(3) Calculate the correlation coefficient matrix R , $R = (r_{ij})_{m \times m}$. The R is a statistical indicator of the closeness of the correlation between the data. The formula is as follows:

$$r_{ij} = \sum\nolimits_{k=1}^{n} (x_{ki} - \overline{x}_i)(x_{kj} - \overline{x}_j) \Big/ \sqrt{\sum\nolimits_{k=1}^{n} (x_{ki} - \overline{x}_i)^2 \sqrt{b^2 - 4ac} \sum\nolimits_{k=1}^{n} (x_{kj} - \overline{x}_j)^2} \tag{3}$$

(4) Compute the characteristic root $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m > 0$ of the characteristic equation $\det\left(R - \lambda E\right) = 0$ of R .

(5) The variance contribution ratio, determining the number of principal components p , i.e:

$$\frac{\sum\nolimits_{i=1}^{p} \lambda_i}{\sum\nolimits_{i=1}^{m} \lambda_i} \geq \alpha \tag{4}$$

where α is determined according to the actual problem.

(6) Calculate p corresponding unit eigenvectors, i.e:

$$\beta_1 = \begin{bmatrix} \beta_{11} \\ \beta_{21} \\ \cdots \\ \beta_{m1} \end{bmatrix}, \beta_2 = \begin{bmatrix} \beta_{12} \\ \beta_{22} \\ \cdots \\ \beta_{m2} \end{bmatrix}, \ldots, \beta_p = \begin{bmatrix} \beta_{1p} \\ \beta_{2p} \\ \cdots \\ \beta_{mp} \end{bmatrix} \tag{5}$$

(7) Calculate the principal components, i.e:

$$Z_1 = \beta_{1i} X_1 + \beta_{2i} X_2 + \ldots + \beta_{mi} X_m \; \left(i = 1, 2, \ldots, p\right) \tag{6}$$

(8) Determination of indicator weights. Calculate the cumulative contribution rate of variance F_i for each factor in each time period, the cumulative contribution rate of variance represents the degree of influence of each principal component. Standardize the eigenvalues of the retained principal components according to the proportion of each eigenvalue λ_i to the sum of the eigenvalues of the retained principal components in order to determine the weight of each principal component, i.e.:

$$z^* = \frac{\lambda_i}{\sum\nolimits_{i=1}^{n} \lambda_i} \tag{7}$$

where z^* is the i th principal component weight, λ_i is the i th principal component variance contribution ratio, and n is the number of retained principal components.

2.2. Decision Tree Based Modeling

2.2.1. Theoretical foundations of decision tree algorithms

(1) Decision Tree Algorithm

Decision Tree (DT) is a powerful machine learning algorithm which is a non-parametric supervised learning method for classification and regression tasks. It creates a model by learning a sample dataset to obtain some decision rules to predict the value of the target variable. Decision trees are very easy to understand and explain due to sharing internal decision logic [32].

The basic algorithmic logic of decision trees is to construct a tree structure by dividing the data set, continuously and recursively, with each node representing an attribute and dividing the data set into subsets according to their values until the division cannot be continued. In the decision tree construction process, the Gini index, information entropy and information gain are usually used to select the division attributes, in order to make the division of the subset as pure as possible, that is, the samples of the same category are divided into the same subset. The classification process of the decision tree starts from the root node, traverses downward according to the values of the attributes, and finally reaches the leaf nodes, which represent the classification results.

The main methods for selecting features for decision trees are information gain and Gini index. The information entropy proposed by Shannon represents a measure of uncertainty about a random variable X. The higher the entropy, the more information there is, and vice versa. The formula for information entropy is expressed as:

$$E(s)=\sum_{i=1}^{n}-p_i \log_2 p_i \tag{8}$$

Where s is a random variable, n is the number of values of s, and p_i denotes the probability of each value.

Information gain is further evolved from information entropy, and the essence of information gain is the measure of the degree of change of information entropy, which is calculated as:

$$Gain(S,A)=Entropy(S)-\sum_{v\in Values(A)}\frac{|S_v|}{|S|}Entropy\left(S_v\right) \tag{9}$$

where S is a set of instances, A is a feature, S_v is a subset of S, $A=v$, and $Values(A)$ is the set of all possible values of A.

The Gini index is used to measure the likelihood of a randomly selected sample being misclassified by a node, and its value is always between 0 and 1. 0 means that all elements belong to a certain classification, 1 means that all elements are randomly distributed in each classification, and 0.5 means that the elements are uniformly distributed in the class. The Gini index is calculated using the formula:

$$Gini=1-\sum_{i=1}^{n}p_i^2 \tag{10}$$

(2) Decision tree pruning strategy

Decision tree is not the more “leafy” the better, when a decision tree reaches a certain depth and then split downward, the results are not more refined but the error rate increases. It is necessary to choose the appropriate depth of the tree before generating a decision tree, pruning rule is used to compensate for the occurrence of overfitting method for correction. The pruning strategy of decision tree mainly consists of pre-pruning and post pruning, pre-pruning is to estimate and then divide, post pruning is to construct the whole decision tree first, and then examine the non-leaf nodes from the bottom upwards [33].

Post-pruning is realized by loss function, in the pruning process, the loss function of subtree T is:

$$C_\alpha(T)=C(T)+\alpha\left|T\right| \tag{11}$$

Where T is an arbitrary subtree, $\alpha(\alpha\geq 0)$ is the regularization parameter, which weighs the degree of fit of the training data and the complexity of the model; $C(T)$ is the prediction error of the training data, and $\left|T\right|$ is the number of leaf nodes of the subtree T.

When $\alpha=0$ there is no regularization, i.e., the original decision tree is the optimal subtree, and when α gradually increases, then the greater the strength of regularization, the smaller the generated optimal subtree is compared to the original subtree. When $\alpha=\infty$, i.e., the regularization strength reaches the maximum, then the single-node tree composed of the root nodes of the original decision tree is the optimal subtree. Thus for a fixed α, it follows from the loss function of the subtree that there must exist a unique subtree T_α that minimizes the loss function $C_\alpha(T)$, and T_α is optimal in the sense of minimizing the loss function.

The decision tree can be pruned by recursive methods. Increasing α from small to large, $0 < \alpha_0 < \alpha_1 < \ldots < \alpha_n < +\infty$, produces a series of intervals $[\alpha_i, \alpha_{i+1})$, with $i = 0, 1, \ldots, n$; the pruning yields a sequence of subsets corresponding to the interval $\alpha\ in[\alpha_i, \alpha_{i+1})$ of the optimal subtree sequence $\{T_0, T_1, \ldots, T_n\}$.

Pruning from the original decision tree T_0, for any internal node t of T_0, the loss function with t as a single node tree can be expressed as:

$$C_\alpha(t) = C(t) + \alpha \tag{12}$$

The loss function of the subtree T_t with t as the root node is:

$$C_\alpha(T_t) = C(T_t) + \alpha \mid T_t \mid \tag{13}$$

When $\alpha = 0$ and α is sufficiently small (the optimal subtree is the original decision tree), there are inequalities:

$$C_\alpha(T_t) < C_\alpha(t) \tag{14}$$

As α increases, there is at a certain α:

$$C_\alpha(T_t) = C_\alpha(t) \tag{15}$$

As α continues to increase (the optimal subtree is a single node tree consisting of the root node), there is:

$$C_\alpha(T_t) > C_\alpha(t) \tag{16}$$

When the loss function of T_t is equal to that of t i.e. $C_\alpha(T_t) = C_\alpha(t)$, the association yields α denoted by:

$$\alpha = \frac{C(t) - C(T_t)}{\mid T_t \mid - 1} \tag{17}$$

Since t has fewer nodes, t is more desirable than T_t, so the subtree T_t can be pruned, and all of his children nodes are cut off to become a leaf node t. According to the above equation, the threshold value α for whether each subtree is pruned or not can be calculated, if the value α for whether all nodes are pruned or not is calculated, and then cross-validation is done for the optimal subtrees after pruning corresponding to different α respectively, an optimal α can be selected, and the optimal subtree corresponding to it can be used as the final result after pruning. The result of the pruning will be the optimal subtree of α.

2.2.2. Strategies for generating decision tree models

Decision trees are particularly suitable for multi-class distribution problems, especially in the relevant research process of this paper, which involves quantifying the indicators of strategic decision-making of science and technology enterprises, for any strategic decision-making classification point. Generally speaking, the generation of decision trees is based on a root node, non-terminating nodes and terminating nodes, if a decision tree is represented by a Tree, then a decision tree Tree corresponds to a kind of division of the feature space of the decision tree. In this paper, key strategic decision indicators are used to divide the feature space into certain pre-specified regions, assign a label to each region, and set the threshold value of the label, according to the comparison of the label value and the threshold value, to decide the attribute attribution of the feature space, and thus recursively processed to arrive at the classification results.

According to the pre-set decision rules, each sample is given a clear category, and at the same time, an error matrix is defined, which is used to represent the conditional probability that the samples in this category are categorized into a certain category by the decision rules, and finally, the classification results are obtained. As a result, a categorized decision tree about the strategic decisions of science and technology enterprises can be obtained, which can provide certain path support for the choice of strategic decisions of science and technology enterprises.

2.2.3. Overall framework of decision tree modeling

This paper takes science and technology enterprises as the research object, and makes decisions on science and technology enterprises in strategy optimization through decision tree analysis method. The establishment process of the decision tree model is as follows:

(1) Collect data and information. Collect enterprise financial data, market data, competitors' data and so on. Pre-process the data, including data cleaning, data conversion, etc., to ensure data accuracy and consistency.

(2) Construct decision tree model. In the strategic optimization decision of science and technology enterprises, we consider the cost of science and technology innovation, the benefit of science and technology innovation, the cost of industrial and financial integration, and the benefit of industrial and financial integration. Then, based on these factors, a decision tree model is constructed as shown in Figure 1, which is used to evaluate the advantages and disadvantages of various decision-making options.

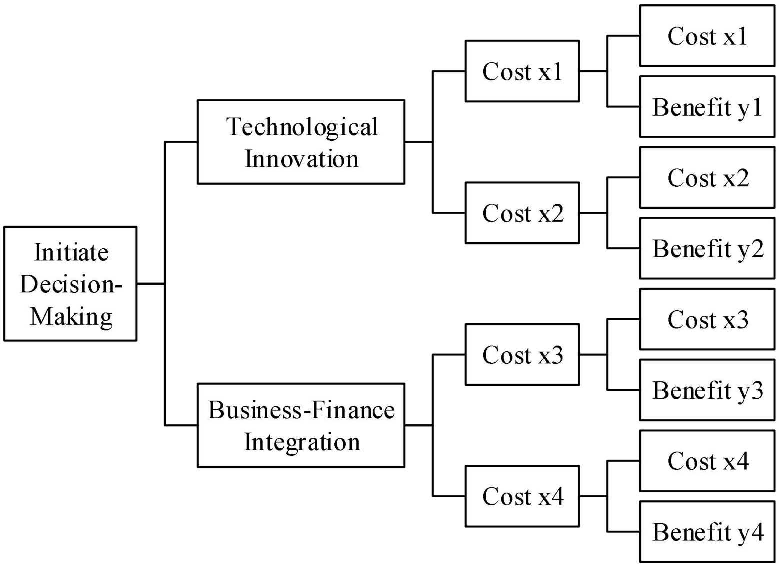

Figure 1. The overall framework of the decision tree model.

In the above model, “x1, x2, x3, x4” represent the possible costs of STI and industry-finance integration, and “y1, y2, y3, y4” represent the possible benefits of STI and industry-finance integration. Then, we can calculate the total cost and total benefit of implementing STI and industry-finance integration by calculating the cost and benefit of each path, and determine which decision-making program is optimal based on the comparison of cost and benefit.

(3) Decision analysis. According to the results of the model, the advantages and disadvantages of various decision-making options are evaluated, and the optimal decision-making option is selected.

2.3. SWOT Matrix for Technology Firms

2.3.1. SWOT Matrix Modeling Theory

SWOT analysis is a more commonly used strategic analysis tool that includes analyzing the strengths, weaknesses, opportunities and threats of an enterprise, and its specific framework is shown in Figure 2. It actually takes the external factors (opportunities and threats) and internal factors (strengths and weaknesses) faced by the enterprise into account in a comprehensive manner, making the analysis more comprehensive and representative.

Figure 2. schematic diagram of SWOT analysis model.

While the analysis of strengths and weaknesses focuses on observing the company's own strengths and comparisons with its competitors, the analysis of opportunities and threats pays more attention to the impact that changes in the external environment may have on the company. So in the process of analysis, we will focus on all the internal factors together which are our strengths and weaknesses, and then come to analyze the impact that the external forces may have on these factors.

Environmental threats are the unfavorable effects of the business environment on the business operations. If left unchecked, this adverse effect will result in a decrease in the company's profitability and a weakening of its ability to compete. Environmental opportunities are those where the business environment has a very favorable impact on the company's growth and enhances the company's continued profitability. When two competing firms offering the same or similar services or products in the same operating environment, we consider one firm to have a competitive advantage over the other when it has higher profitability as well as potential. A company can only target its strengths and avoid its weaknesses if it knows what its strengths are. The biggest problem here is actually the attitude of the company in maintaining its competitive advantage.

2.3.2. Selection of enterprise research subjects

Y Technology Company is located in N City, the capital city of J Province. N City, as an important city in the Yangtze River Delta region, has been laying out the biomedical industry for a long time, and Y Technology Company is specifically located in JN District, which has always been the first in terms of economic volume in N City, and has exceeded the trillion-dollar mark in recent years. After years of good operation, Y-Tech has been playing the role of the main position of JN District's biomedical incubator in attracting talents, gathering talents and cultivating enterprises.

Y Science and Technology Company was established in 2012, including state-owned, private capital of the multi-investment body funded. The incubation service team covers finance, science and technology, management and other multi-disciplinary specialties. After years of good operation, it has played the role of a biomedical incubator as the main position for attracting talents, gathering talents and cultivating enterprises. It has formed a gathering point for big health and new medicine enterprises, mainly in chemical drug research and development, biotechnology, cell therapy and high-end medical devices. Y-Tech adopts the operation mode of “incubator + common technology platform” to build a municipal public technology platform with professional service qualification for the weakest technology integration and industrial amplification in the process of science and technology industrialization. The platform integrates talents, technologies and equipments, aiming to provide professional services for enterprises and units related to innovation and entrepreneurship, transnational technology transfer, industry-university-research and R&D outsourcing in the field of life sciences industry, which covers two major common platforms, namely, drug R&D and biotechnology.

Y Technology Company already has a certain degree of reputation and recognition in the industry. Since its establishment, Y Technology Company has independently cultivated 7 listed enterprises, 2 unicorn enterprises, 9 cultivated unicorn enterprises, 6 specialized small giants and 9 gazelle enterprises. On the whole, the overall development momentum of Y Technology Company is better, and its strategic development layout is in a more balanced state under the intertwining of internal and external environments.

2.3.3. SWOT Matrix Model Analysis

Taking Y Technology Company as the research object, using SWOT model, combining its internal and external environmental factors, through the analysis of Y Technology Company's internal ability conditions and core resources, as well as the detailed study of the market and the industry, it can be concluded that the results of Y Technology Company's strategic matching are shown in Table 2.

Table 2. Strategy matching of Y technology companies.

-	Strengths: 1. Good financial capacity status. 2. Strong professional technical strength. 3. The quality of human resources is excellent. 4. The relationship between the government and enterprises is good.	Weaknesses: 1. Insufficient brand recognition. 2. The construction of corporate culture is incomplete. 3. The management system is not perfect enough. 4. The product cost is relatively high.
Opportunities: 1. The country has issued relevant policies to support the development of the industry. 2. The market is broad and the potential is huge. 3. There is no such phenomenon as an oligopoly in the industry. 4. The industry forms a cluster posture.	SO strategy: 1. Utilize the existing policy environment to apply for corresponding industrial projects and talent programs. 2. Form a high-quality marketing team to carry out market expansion and development. 3. Strive to secure demonstration projects for the Internet of Things.	WO strategy: 1. Cooperate with well-known manufacturers to form a scale effect and expand customer resources. 2. Build corporate culture and gradually improve the company's management system. 3. Absorb the excellent experiences of international peers, penetrate into the field of standards, and strive for the initiative in standard formulation. 4. Apply for intellectual property rights and patent protection.
Threats: 1.The technology development is fast and the new generation is new. 2.There is no mature business model yet. 3.The market is competitive.	ST strategy: 1. Establish a form of integration among government, industry, academia and research, carry out advanced research and development, and quickly launch new products. 2. Increase investment in technological research and development, extend to the front end of the industrial chain, and launch overall solutions in areas with better development. 3. Establish rich sales channels and cultivate system integrators and terminal module manufacturers.	WT strategy: 1. Control the scale of the enterprise, reduce costs, and wait for opportunities. 2. Enter the niche market quickly when it just enters the mature stage. 3. Adopt differentiated competitive strategies from large Internet of Things enterprises. 4. When learning and absorbing the experience of foreign technologies, carry out reverse innovation.

(1) SO strategy (growth strategy) is a growth strategy that rationally utilizes external opportunities by reasonably demonstrating the favorable impact of the enterprise's internal resource conditions. The enterprise can utilize its own advantageous conditions to strive for these opportunities, and can use the financial support of these preferential policies to develop the product market and professional technology research and development.

(2) WO strategy (turnaround strategy) refers to the adoption of reasonable use of opportunities in the external environment to achieve the goal of compensating for the shortcomings of the enterprise's internal conditions of a turnaround strategy. It aims to further build up scale effect and industrial alliance clusters, and at the same time, improve the value of corporate culture by absorbing excellent experience and formulating reliable corporate rules and regulations.

(3) ST strategy (multiple business strategies) is a multiple business strategy that reduces or even avoids threats to the enterprise from the external environment by fully and reasonably utilizing the enterprise's internal advantages. It can take advantage of the good relationship between the enterprise and the government units and give full play to the advantages of the enterprise's strong capital and the role of

its own professional and technical team, to establish the form of government, industry, academia and research combination. Increase investment in technology research and development, research and development ahead of time, the rapid introduction of new products to cope with the rapid renewal of products.

(4) WT strategy (defensive strategy) is adopted to reduce the impact of the enterprise's internal conditions in the disadvantage, and can avoid the external disadvantages of a defensive strategy. It can be adopted to reduce the recruitment of employees, control the scale of the enterprise, and set up technology research and development bases in second- and third-tier cities in order to reduce costs. It is also possible to learn from the experience of absorbing foreign technology and carry out reverse innovation to come up with real low-cost and high-quality solutions.

3. Application of strategic decision-making models for science and technology enterprises

In today's era, the intensity of inter-enterprise competition continues to escalate, the unevenness of the market is becoming more and more prominent, all of which makes the opportunity for strategic adjustment of enterprises more and more fragmented, the once-and-for-all traditional corporate strategy can no longer adapt to the era of rapid change, the window of opportunity for enterprises to make strategic adjustments to the window of opportunity to close more and more quickly. In an era full of uncertainty and frequent conflicts, rapid adaptability has become the most important survival ability of an organization, and the response speed of an enterprise to strategic change has become a key factor in determining the fate of the enterprise. Based on the results of SWOT matrix model analysis, this chapter introduces the decision tree model to further analyze the specific paths suitable for strategic innovation of science and technology enterprises, and to provide support for further enhancing the market competitiveness of science and technology enterprises.

3.1. Analysis of strategic choices for science and technology enterprises

3.1.1. Questionnaire design and reliability analysis

In selecting the SWOT strategy of Y Technology Company, this paper establishes a questionnaire based on the strategic decision-making index system of science and technology enterprises. The questionnaire is mainly to choose 50 strategic planning experts who are more authoritative in the field of science and technology as the survey object, and the questionnaire is all completed through online. A total of 50 questionnaires were issued, and 50 were effectively recovered to provide data support for the SWOT strategy selection of science and technology enterprises.

After obtaining the questionnaire data, it is necessary to further verify the reliability of the questionnaire data. Reliability analysis is to analyze the reliability of the data, i.e., using Cronbach's alpha coefficient for testing. Validity analysis, on the other hand, utilizes KMO and Bartlett's test of sphericity. Generally when the KMO value is greater than 0.75 and the Bartlett's sphericity test is significantly lower than 0.05, it means that the questionnaire passes the validity test.

The questionnaire data were organized to obtain the overall Cronbach's α coefficient of the questionnaire was 0.941, and the Cronbach's α coefficient of each index was greater than 0.85, which indicated that the questionnaire involved in this paper had a good reliability coefficient, passed the reliability test, and could be further analyzed. In addition, the validity test found that the KMO value is 0.904, which proves that the sample adequacy is high and suitable for analysis, and the significance given by the Bartlett's test of sphericity is 0.000, which meets the standard of the level of significance, so the questionnaire designed in this paper passes the requirements of the validity test.

3.1.2. Principal component analysis of strategic indicators

After carrying out the validity test, the KMO and Bartlett's sphericity test indicate that the strategic decision-making indicators of science and technology enterprises are suitable for extracting the common factor and there is a high degree of correlation. Based on the data of the questionnaire, combined with the application steps of principal component analysis, the variance of the common factor of strategic decision-making indicators of science and technology enterprises is obtained as shown in Table 3. The original value is the value of the initialization of the variable statement, when the value is equal to 1.0 indicates that it can explain all the variance, and the right side represents the degree of variance explanation, in general, the value is greater than 0.55 can be extracted for the common factor. As can be seen from the common degree after extraction in the last column, all the indicators of strategic decision-making in science and technology enterprises obtain a common degree greater than 0.75 after extraction of the common factor, so it is very suitable for the extraction of the common factor.

Table 3. The variance of the common factor of strategic decision-making indicators.

Second index	Code	Common degree	
		Initial	Extract
Eva indicator	PA1	1.000	PA1
Receivable turnover	PA2	1.000	PA2
Inventory turnover	PA3	1.000	PA3
Total asset turnover	OE1	1.000	OE1
Strategic plan completion rate	OE2	1.000	OE2
Turnover of current assets	OE3	1.000	OE3
Project management	IC1	1.000	IC1
Integrated management	IC2	1.000	IC2
Customer sentiment system construction completion rate	IC3	1.000	IC3
Customer satisfaction	CM1	1.000	CM1
R&D schedule and planning compliance	CM2	1.000	CM2
New product customer growth	CM3	1.000	CM3
Research and development team job satisfaction rate	TC1	1.000	TC1
The position is adjusted for the adjustment	TC2	1.000	TC2
Key position talent satisfaction rate	TC3	1.000	TC3
Innovation results increase	TC4	1.000	TC4

Based on the principal component analysis method, the orthogonal maximum rotation method is used to obtain the total variance explanation results of principal component analysis as shown in Table 4, which is ordered according to the importance of the principal component factors in order, and the higher the total value of the overall variance contribution rate in the matrix means that the common factor has a higher degree of explanation for the whole. According to the above table, the characteristic values of the first five components are above 1, and their cumulative contribution rate is greater than 70%, so that means the first five components can explain 70.044% of the overall variance of the original variables, which feeds back a great deal of information about the traditional data.

Table 4. Total variance explanation of PCA.

Factor	Initial eigenvalue			Extraction load			Rotating load		
	Value	Var/%	Sum/%	Value	Var/%	Sum/%	Value	Var/%	Sum/%
1	4.421	27.635	27.631	4.421	27.635	27.631	4.338	27.113	27.113
2	2.329	14.556	42.188	2.329	14.556	42.188	2.269	14.181	41.294
3	1.735	10.844	53.031	1.735	10.844	53.031	1.871	11.694	52.988
4	1.469	9.181	62.213	1.469	9.181	62.213	1.647	10.294	63.281
5	1.253	7.831	70.044	1.253	7.831	70.044	1.082	6.763	70.044
6	0.671	4.194	74.238	-	-	-	-	-	-
7	0.642	4.013	78.250	-	-	-	-	-	-
8	0.613	3.831	82.081	-	-	-	-	-	-
9	0.547	3.419	85.500	-	-	-	-	-	-
10	0.503	3.144	88.644	-	-	-	-	-	-
11	0.432	2.700	91.344	-	-	-	-	-	-
12	0.383	2.394	93.738	-	-	-	-	-	-
13	0.322	2.013	95.750	-	-	-	-	-	-
14	0.281	1.756	97.506	-	-	-	-	-	-
15	0.234	1.463	98.969	-	-	-	-	-	-
16	0.165	1.031	100.00	-	-	-	-	-	-

In order to economically interpret the five principal component factors selected, the initial variable loadings on the factors were then calculated, and the factor loading matrices were rotated orthogonally to form a post-transfer loading matrix (the "rotated component matrix" was obtained by means of factor profiling), and the specific results are shown in Table 5. According to the coefficient of each factor, the variable can be seen in the factor loadings, usually greater than 0.6 belongs to the factor. Factors 1~5 contain the dimensions of profitability, operational efficiency, system construction, customer management and talent cultivation respectively, and the factor loadings corresponding to the above variables are all greater than 0.8, which are basically similar to the factor dimensions of the strategic decision-making index system established in the previous section.

Table 5. Principal component factor load matrix.

Code	Principal component factor payload				
	1	2	3	4	5
PA1	**0.918**	0.457	0.231	0.257	0.318
PA2	**0.863**	0.375	0.234	0.213	0.362
PA3	**0.816**	0.214	0.222	0.371	0.379
OE1	0.218	**0.865**	0.357	0.250	0.392
OE2	0.337	**0.856**	0.430	0.376	0.204
OE3	0.266	**0.932**	0.233	0.220	0.357
IC1	0.418	0.424	**0.882**	0.458	0.299
IC2	0.434	0.314	**0.856**	0.300	0.263
IC3	0.411	0.476	**0.845**	0.315	0.346
CM1	0.256	0.248	0.385	**0.858**	0.413
CM2	0.274	0.352	0.396	**0.874**	0.302
CM3	0.287	0.317	0.398	**0.888**	0.425
TC1	0.258	0.426	0.309	0.284	**0.885**
TC2	0.313	0.419	0.312	0.250	**0.897**
TC3	0.432	0.238	0.393	0.280	**0.815**
TC4	0.341	0.380	0.474	0.201	**0.903**

3.1.3. SWOT Strategy Options for Firms

Through the application of the principal component analysis method, the total ranking of the weight value of the degree of influence of the second-level indicators on the first-level indicators in the strategic decision-making index system of science and technology enterprises can be calculated. At this point it is possible to use the results of the weight value calculation to make strategy selection for the strategic decision-making of science and technology enterprises. When choosing, the weights of the factor indicators with the greatest degree of influence are expressed in the strategic choice coordinate axis of the SWOT quadrilateral, and then connected sequentially to form a quadrilateral. From the total weight calculation results, we can conclude that the factors with the largest weights at the indicator level are total asset turnover rate (OE1), integrated management system (IC2), comprehensive customer satisfaction rate (CM1), and key position talent satisfaction rate (TC3), with their weights being 0.427, 0.148, 0.095, and 0.036 respectively. Then the SWOT quadrilateral strategy selection coordinate system is shown in Figure 3.

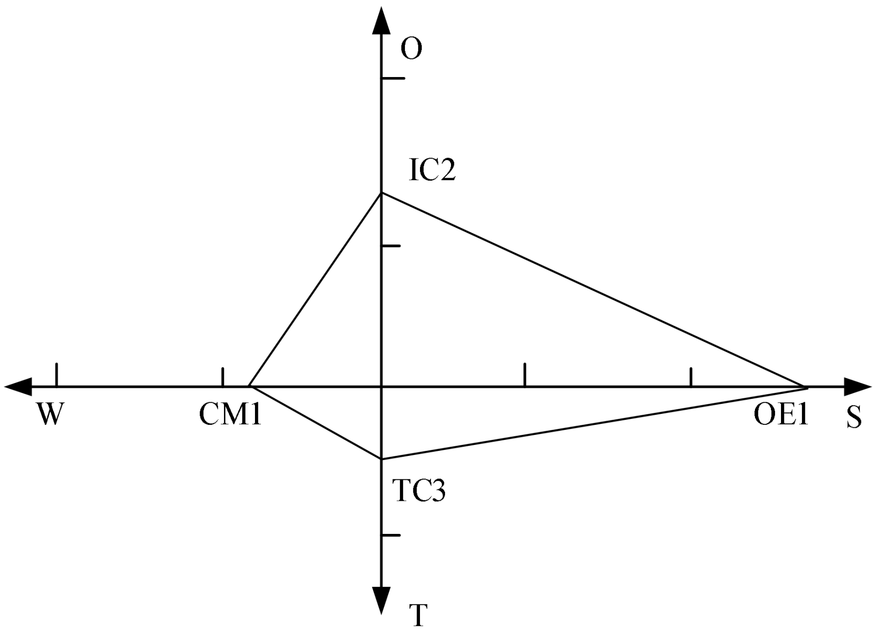

Figure 3. SWOT Quadrilateral strategy selection coordinates.

According to Figure 3, the area of the triangles in each quadrant is calculated separately as follows:

Area of the first quadrant = OE1*IC2*1/2 = 0.427*0.148*1/2 = 0.0316;

Area of the second quadrant = IC2*CM1*1/2 = 0.148*0.095*1/2 = 0.0070;

Third quadrant area = CM1*TC3*1/2 = 0.095*0.036*1/2 = 0.0017;

Area of the fourth quadrant = TC3*OE1*1/2 = 0.036*0.427*1/2 = 0.0077;

The order of magnitude of the above triangular areas is first quadrant > fourth quadrant > second quadrant > third quadrant. So, the order of strategy optimization choices for ST firms is SO strategy, ST strategy, WO strategy, WT strategy in that order. Therefore, for the strategic choice of Y technology formula, its optimal strategy is SO strategy, i.e., a kind of growth strategy that rationally uses external opportunities by reasonably displaying the favorable influence of the internal resource conditions of the enterprise.

3.2. Test results of the decision tree model

3.2.1. Decision Tree Model Classification Accuracy

First, this paper equalizes the predicted variable strategic decision choice (Strategic), and constructs a baseline model that includes external environment and internal features of the enterprise, as well as a full model that includes all features. Second, in terms of parameter setting, the decision tree model parameter setting mainly involves the minimum value of the sample size covered by the leaf nodes, which involves the trade-off between the model generalization ability and the classification accuracy. Based on the number of samples, this paper sets the minimum value of the sample size covered by leaf nodes to 20 to ensure that the generated decision tree has a high generalization ability and prediction accuracy. Finally, in the selection of prediction methods, the prediction method chosen in this paper is the ten-fold cross-validation method. Compared with the method of randomly dividing the training set and test set, the prediction results of the ten-fold cross-validation method are less interfered by the randomness of the division, and the results are reproducible. In this paper, the logistic regression model (LR) is also chosen as a comparison, and the classification accuracy of different models is obtained as shown in Table 6. Among them, the training accuracy can reflect the model's ability to classify the dataset, and the test accuracy, expressed as the mean of the accuracy of ten-fold crossover, can reflect the model's ability to predict the strategic optimization choices of science and technology enterprises.

Through the analysis, it is found that compared with the benchmark model, the full model improves in training performance and prediction performance, so as to judge the contribution of strategic decision indicators to the prediction of strategic optimization choices of science and technology enterprises. Meanwhile, a comparison of the decision tree with traditional logistic regression shows that. First, the machine learning method based on decision tree can better predict the strategic optimization choice of science and technology enterprises, and both the benchmark model and the full model have high prediction accuracy. Among them, the model training accuracy is 72.51% and 76.04% respectively, and the test accuracy under ten-fold crossover is 64.49% and 69.78% respectively, indicating that the features of the strategic decision indicator selected in this paper have a good prediction effect on the strategic optimization choices of science and technology enterprises. Second, compared with the logistic regression method, the decision tree can improve the model prediction accuracy to a larger extent. Compared with logistic regression, its accuracy is improved by 9.14% and 5.76% in the baseline model, and 13.89% and 11.39% in the full model, indicating that decision trees are more suitable for dealing with complex prediction problems.

In addition, strategic decision features contribute significantly to the prediction of strategic optimization choices of science and technology enterprises. After adding strategic decision features, the model training accuracy and testing accuracy are improved by 3.53% and 5.29% respectively, indicating that strategic decision features can predict the strategic optimization choices of technology enterprises to a certain extent. After adding strategic decision features in logistic regression, the accuracy of the full model decreased, indicating that the influence of strategic decision features on the strategic optimization choices of science and technology enterprises may have non-linear characteristics, and thus it is more appropriate to choose the decision tree model to analyze the relationship between variables.

Table 6. Classification accuracy of different models.

	Benchmark Model (1)		Full model (2)		(2) - (1)	
	Train	Test	Train	Test	Train	Test
DT	72.51%	64.49%	76.04%	69.78%	3.53%	5.29%
LR	63.37%	58.73%	62.15%	58.39%	-1.22%	-0.34%
Lifting rate	9.14%	5.76%	13.89%	11.39%	-	-

3.2.2. Decision tree models for strategy optimization

In Section 3.2.1, we calculated the training accuracy of the decision tree as a whole and the testing accuracy of the ten-fold cross-validation. Relying on the model data, this section further draws the structure of the decision tree model about the strategic optimization choices of science and technology enterprises, and then reveals the influence of the joint effect of the five strategic decision indicators on the strategic optimization choices of science and technology enterprises. Figure 4 shows the decision tree of the influence mechanism of strategic optimization choices of science and technology enterprises. In the figure, ovals are the features used for splitting, rectangles are the output leaf nodes, and in the leaf nodes, the words in front of the parentheses show the final category of the leaf nodes, where “High” means high strategic optimization choice, and “Low” means low strategic optimization choice. choice. The first number in parentheses represents the total number of samples contained in the leaf node, and the second number represents the misclassification, i.e., the number of samples that are not in the final category of the leaf node.

As shown in the figure, for example, High(127,18), which indicates that the leaf node category is High Strategic Optimization Choice, the node contains a total of 127 samples, of which 18 samples have the actual category of Low Strategic Optimization Choice, then the classification accuracy of this leaf node is (127-18)/127=0.858. A total of the following six rules can be obtained from the figure. Namely:

(1) When technology firms have low profitability and low operating efficiency, then technology firms have high strategic optimization choices.

(2) When technology firms have low profitability and high operational efficiency, then technology firms have low strategic optimization options.

(3) When the technology enterprise has high profitability and good system construction, but poor customer management, then the technology enterprise has low strategic optimization choice.

(4) When the technology enterprise has high profitability and good system construction, and customer management is excellent, then the technology enterprise has high strategic optimization choice.

(5) When a technology company has high profitability but weak system construction and poor talent development, then the technology company has a low strategic optimization choice.

(6) When a technology company has high profitability, weak system construction but excellent talent development, then the technology company has a high strategic optimization choice.

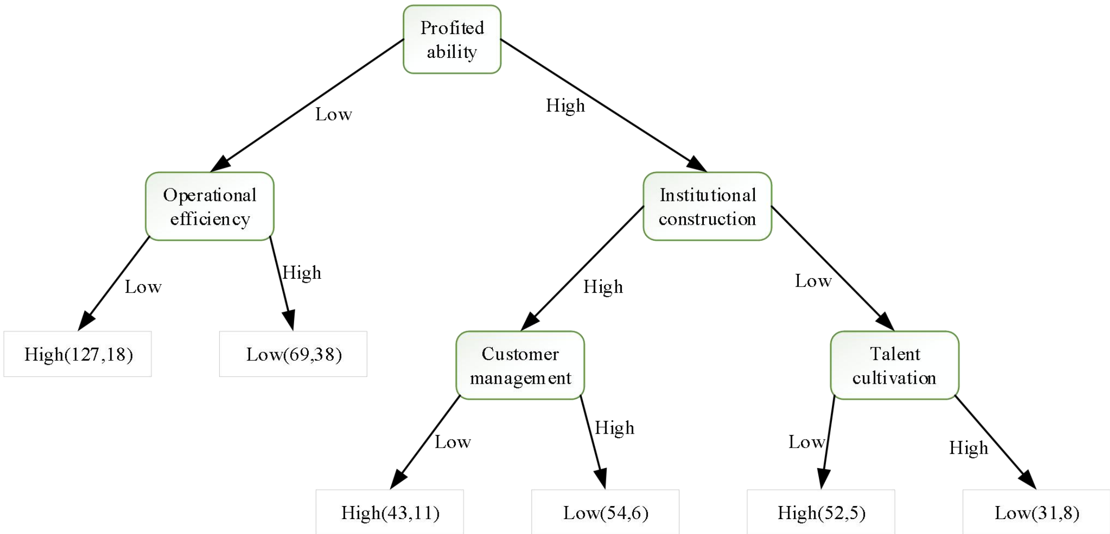

Figure 4. Decision tree model for strategic optimization.

4. Conclusion

This study aims to improve the decision-making ability of science and technology enterprises in the formulation of strategy optimization strategies, which solves the problem that science and technology enterprises are indecisive under different strategic indicators, and guides the direction of strategy optimization choices for science and technology enterprises. The article uses principal component analysis to obtain the weights of strategic decision indicators, and combines the SWOT matrix model to analyze the focus of different strategies of technology enterprises, and then inputs the data into the decision tree model to make predictions on the optimization of enterprise strategies. The accuracy of the decision tree model in predicting the strategic optimization choices of science and technology enterprises can reach up to 76.04%, which is significantly higher than the accuracy of logistic regression. Relying on the decision tree model, multiple paths can be obtained to meet the strategic optimization choices of science and technology enterprises, which can provide support for improving the strategic innovation of science and technology enterprises.

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