International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 3124-3138

https://doi.org/10.70517/ijhsa463262

# Optimizing the Commercial Operation and Development Path of Sports Industry Using Linear Programming Models

**Chenchen Lv[1,2,*], Yifeng Wang[2] and Jin Chai[1]**
[1] School of Sports Economics and Management, Xi'an Physical Education University, Xi'an, Shaanxi, 710068, China
[2] School of Economics & Management, XIDIAN University, Xi'an, Shaanxi, 710126, China
Corresponding authors: (e-mail: lvchenchen24@stu.xidian.edu.cn).

**Abstract** This paper proposes a comprehensive method system integrating linear programming model, fuzzy compromise planning and decision tree algorithm, aiming to optimize the commercial operation and development path of sports industry. By constructing an interactive simulation framework based on the economic indicator model, it supports users to dynamically adjust the objective variables and policy constraints to achieve multi-objective optimization. Aiming at the problem of goal conflict and ambiguity, the affiliation function is introduced to quantify the goal satisfaction, and combined with the payment matrix and global utility function, the multi-objective optimization is transformed into a fuzzy planning problem. The decision tree algorithm CART is further used to optimize feature selection and improve the classification and regression prediction accuracy. Experiments show that the average running time of the CART algorithm is only 165.88 seconds, and the maximum fitness value reaches 1600, which is significantly better than the traditional genetic algorithm (more than 200 seconds) and ID3 and C4.5 algorithms. Based on the 2015-2024 sports industry data, the model consistency test shows that the simulation error of the total revenue of the sports industry is lower than 3.32%, and the error of the event-related revenue is generally lower than 6%, which verifies the effectiveness of the model. The sensitivity analysis shows that a 30% increase in the proportion of government financial support can increase the total revenue of the sports industry to 7.40 trillion yuan (+30.8%) in 2024, and a 30% increase in the proportion of sponsor investment can drive the revenue to 8.20 trillion yuan (+44.9%). The study provides data-driven decision support for sports industry resource allocation, risk analysis and policy formulation.

**Index Terms** linear programming, sports industry, business operations, fuzzy compromise planning, CART decision tree

## I. Introduction

With the development of society, the sports industry is rapidly emerging and becoming a prosperous industry [1], [2]. Sports industry is an important industry in China's economic and social development, with a special status and role [3], [4]. China's sports industry not only plays a positive role in cohesion of national will, development of national diplomacy and enhancement of national pride, but also plays a positive role in promoting China's economic and social development [5]-[7]. In this industry, sports industry commercial operation and development path play a crucial role, sports commercial operation refers to the combination of sports industry and commercial operation, through sports events, fitness clubs, sporting goods sales, etc., to realize the double growth of economic and social benefits, and the development path is to promote the sports industry commercial development strategies, ways and means [8]-[11]. And the optimization of sports industry commercial operation and development path is of great significance for the sustainability of sports industry commercial development [12], [13].

Linear programming is a common optimization problem solving method in operations research, which can use mathematical models to describe complex economic, engineering, management and other problems, and seek the optimal decision-making scheme under the premise of satisfying constraints [14], [15]. In the optimization of commercial operation and development path of sports industry, linear programming can be applied to resource allocation, production planning, inventory management, logistics and distribution, etc., to provide support for enterprises to seek optimal decision-making, so as to better promote the development of sports industry [16], [17].

The article proposes a comprehensive method system integrating linear planning model, fuzzy compromise planning and decision tree algorithm, aiming to optimize the planning and execution path of commercial projects in sports industry through the combination of quantitative analysis and intelligent decision-making tools. The study constructs an interactive simulation framework based on the economic indicator model through the decision-making assistance analysis of commercial projects in sports industry, which supports the users to dynamically adjust the plan and implement it by setting target variables (e.g., output growth rate, profit growth rate) and policy constraints (e.g., tax incentives, financial budget). To address the problem of multi-objective conflict and ambiguity, fuzzy compromise planning is introduced to quantify the target satisfaction through the affiliation function, combined with the payment matrix and global utility function, transforming the multi-objective optimization into a fuzzy planning problem to ensure that the decision-making results are balanced between economic and social benefits. Combined with the principle of decision tree algorithm, the feature selection is optimized by using indicators such as information entropy and Gini index to improve the accuracy of classification and regression prediction, which provides data-driven support for risk analysis and prioritization of sports industry projects.

## II. Construction of multi-objective optimization model for commercial operation of sports industry based on linear programming

### *II. A. Decision Aid Analysis for Business Project Establishment in Sports Industry*

The Decision Aid and Analysis Function for Sports Industry Business Projects is designed to provide planning and decision makers with analytical aids to identify project options and optimize them to meet the expected economic development goals of the sports industry.

Around this purpose, the function adopts an interactive working method, and the basic mode is that the user establishes clear quantitative indicator variables and preliminary project proposals, and then carries out simulations under different conditions based on the economic indicator model, and then determines the project proposals based on the results of the simulations.

The specific working method and steps of this function are as follows.

First, the user of the governmental management department sets a set of target variables for the economic development of the commercial operation of the sports industry as the expected goal of the policy program, and selects the output growth rate, profit growth rate, asset growth rate, or employment growth rate of the sports industry, and so on. The set of indicators can be directly adopted from the data variables in the basic information data set, or can be based on the derived variables of these basic variables.

In the second step, the user initially identifies a set of supported sports product ranges based on experience. At the same time, the user identifies targeted support methods, i.e., policy variables, such as tax credit ratios, credit facility interest rate concessions or subsidy ratios, and the amount of direct science and technology targeted input funding. At the same time, the user determines the total constraints on the budgetary conditions of the above policy options based on the overall level of financial support from the government.

In the third step, the user carries out a simulation analysis based on the measurement model based on the above target variables and conditional constraints. There are two basic types of analysis and calculation: the first type is to calculate the corresponding policy variables such as the level of financial support for a given development goal based on model analysis, and the second type is to calculate the level of development goal variables expected to be achieved based on model analysis for a given level of policy variables. On the basis of the above analysis, the user adjusts the level of the objectives or policy variables to determine the optimal program to achieve the desired objectives. The program serves as the basic scope or direction for determining specific project support.

The industry-economic development model for the economic indicator variables of the sports industry is the basis for the above calculation and analysis functions. The model consists of a set of sub-models, each of which describes the correlation of a set of industry-specific economic variables, such as the input-output model of the local sports industry, and the quantitative relationship between the output value and the level of capital input, the level of labor and the level of its factors of production in each industry based on the logarithmic regression model, where the regression coefficients are calculated based on actual data from the past time (e.g., five years) according to the standard statistical algorithm of econometrics. At the same time, the output of each group of models can be used as exogenous variables or environmental variables of other models, based on which a quantitative representation of the relationship between the elements inherent in the changes in the economic development of the sports industry is obtained.

The above is the main working method of the auxiliary analysis function for planning and decision-making of sports industry commercial operation and economic development projects. Accompanying this is a set of auxiliary management functions for the commercial economic model of sports industry, including parameter maintenance, parameter updating and model upgrading management for the numerical model of production and economic variables.

The use case model of the auxiliary analysis of the sports industry and economic project decision-making is shown in Figure 1.

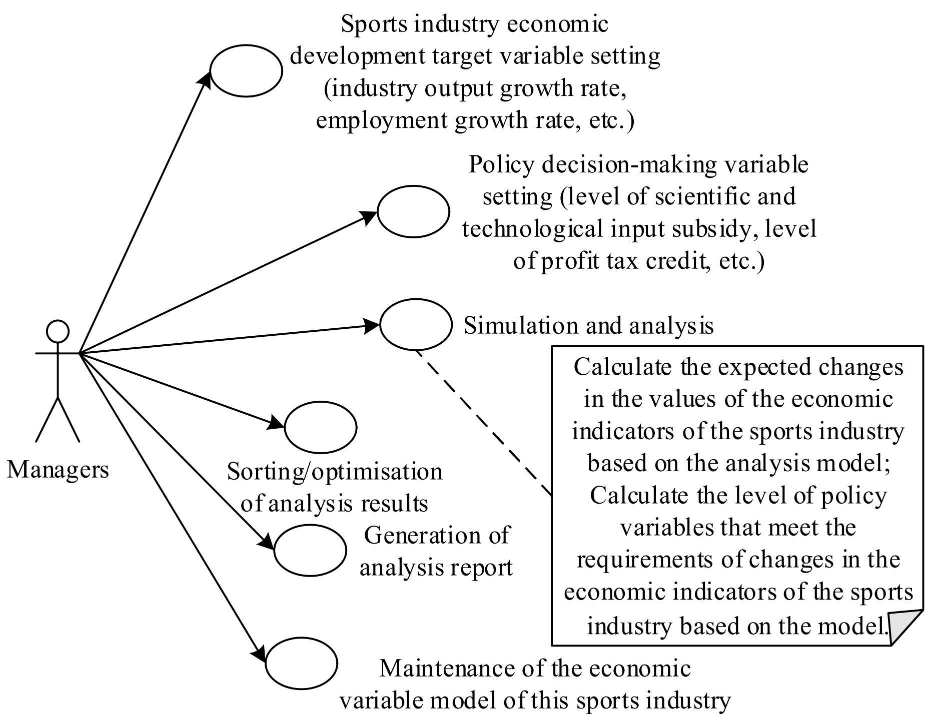


Figure 1: Sports industry economic project proposal decision aid analysis use-Case

### *II. B.Fuzzy compromise planning*

Although the project decision aid analysis can determine the preliminary scheme of commercial operation of sports industry through economic modeling, in practical application, the conflict between objectives and the ambiguity of policy constraints often lead to the difficulty of applying the traditional linear planning model directly. For this reason, it is necessary to introduce the fuzzy compromise planning method to quantify the fuzzy boundaries of the objectives through the affiliation function to provide a more flexible decision-making framework for multi-objective optimization.

#### II. B. 1) Affinity function

The affiliation function $\mu_{\tilde{A}}(x)$ of element $x$ in fuzzy set $\tilde{A}$ is a mapping from the domain $X$ to the real interval $[0,1]$, i.e., $\mu_{\tilde{A}}(x): X \to [0,1]$. Then

$$\tilde{A} = \left\{(x, \mu_{\tilde{A}}(x)) \mid x \in X\right\} \tag{1}$$

$\mu_{\tilde{A}}(x)$ is the affiliation function on $X$.

When $\mu_{\tilde{A}}(x) = 1$, $x$ belongs to fuzzy set $\tilde{A}$ completely; when $\mu_{\tilde{A}}(x) = 0$, $x$ does not belong to fuzzy set $\tilde{A}$ at all.

The article gives three basic concepts of fuzzy goals, fuzzy decisions and fuzzy constraints, which are briefly introduced one by one below.

#### II. B. 2) Fuzzy goals and fuzzy constraints

Fuzzy goal $\tilde{G}$ is some kind of unspecified requirement of the decision maker on the goal, denoted as a fuzzy set on the strategy set $X$, with an affiliation function $\mu_{\tilde{G}}(x): X \to [0,1]$, which responds to the degree of satisfaction that the strategy $x$ can achieve with respect to the goal $\tilde{G}$.

Fuzzy constraint $\tilde{C}$ is an unstrict restriction on the operation of the strategy, denoted as a fuzzy set on the strategy set $X$, with an affiliation function $\mu_{\tilde{C}}(x): X \to [0,1]$, indicating the degree to which the strategy $x$ complies with the constraint.

### II. B. 3) Fuzzy decision making

Fuzzy decision $\tilde{D}$ is also a fuzzy set on the set of strategies $X$, defined as the intersection of fuzzy goals and fuzzy constraints, i.e., $\tilde{D}=\tilde{G}\cap\tilde{C}$, with an affiliation function:

$$\mu_{\tilde{D}}(x)=\min\left\{\mu_{\tilde{G}}(x),\mu_{\tilde{C}}(x)\right\} \tag{2}$$

The concept of fuzzy decision making can be visualized from Figure 2.

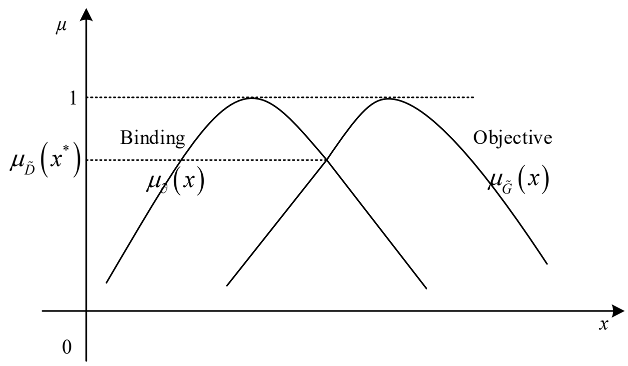


Figure 2: Fuzzy decision-making

According to the three basic concepts of fuzzy objective, fuzzy decision and fuzzy constraints given, fuzzy planning can be roughly categorized into (1) objectives and constraints with explicit parameters; (2) objectives with fuzzy parameters and constraints with explicit parameters; (3) objectives with explicit parameters and constraints with fuzzy parameters; and (4) objectives and constraints with fuzzy parameters.

We assume the general form of the multi-objective planning model as follows:

$$\begin{cases}\min f_1(x_1,\dots,x_n)\\ \dots\quad\dots\quad\dots\\ \min f_r(x_1,\dots,x_n)\\ \max f_{r+1}(x_1,\dots,x_n)\\ \dots\quad\dots\quad\dots\\ \max f_k(x_1,\dots,x_n)\\ s.t.\quad g_j(x_1,\dots,x_n)\le 0, j=1,\dots,m_1\\ \qquad\; h_l(x_1,\dots,x_n)=0, l=1,\dots,m_2\end{cases} \tag{3}$$

In the above model $x_1,\dots,x_n$ is the decision variable of the general model of mathematical planning, $f_i(x_1,\dots,x_n)$, $i=1,\dots,k$ are the objective functions of the model, $g_j(x_1,\dots,x_n)\le 0, j=1,\dots,m_1$, $h_l(x_1,\dots,x_n)=0, l=1,\dots,m_2$ are the constraints of the model.

In the multi-objective planning model, although the objective function and constraints are given explicitly, there are often conflicts due to the non-uniformity of the unit of measurement between the objectives, resulting in unsatisfactory results of objective optimization, in order to take into account the interests of all objectives, the decision maker sets the expected value of each objective and finds out the limiting case of the objective, according to the fuzzy decision-making method, the degree of satisfaction of the objective is expressed by the degree of subordinate function, which transforms the multi-objective optimization problem into a fuzzy planning problem with a degree of subordinate function. Optimization problem is transformed into a fuzzy planning problem containing a degree of affiliation function. According to the three basic concepts of fuzzy objective, fuzzy decision-making and fuzzy constraints, we give a unified fuzzy multi-objective optimization model since $h_l(x_1,\dots,x_n)=0$ can be expressed as $h_l(x_1,\dots,x_n)\le 0$:

$$\begin{cases}f_i(x)\to f_i^*, i=1,\dots,k\\ s.t.\quad x\in G=\left\{x\mid g_j(x)\le 0, j=1,\dots,m\right\}\end{cases} \tag{4}$$

where $f_i^*$ denotes the expected value of the $i$ nd objective, and "$\rightarrow$" denotes trying to reach the objective expected value as much as possible. According to the fuzzy compromise planning method proposed by Li and Lai, this section takes the objective function maximization as an example to illustrate the solution process.

Assume that the general mathematical model for finding the maximum value is

$$\begin{cases} \max f_i(x), i=1,\dots,k \\ s.t \quad x \in G \end{cases} \tag{5}$$

The desired optimal value for each objective is

$$f_i\left(x^{i*}\right) = \max_{x \in G} f_i(x), i=1,\dots,k \tag{6}$$

$x^{i*}$ for $f_i(x)$ obtaining the solution of the ideal maximum value, each objective function $f_j(x)$, $j=1,\dots,k$ can form a payment matrix function of order $k \times k$ under different solutions $x^{i*}$ $i=1,\dots,k$ of the ideal optimum value, such that

$$f_{ij} = f_j\left(x^{i*}\right) i, j=1,\dots,k \tag{7}$$

A payment matrix can be formed as follows:

$$\begin{pmatrix} f_1(x^{1*}) & f_2(x^{1*}) & \cdots & f_k(x^{1*}) \\ f_1(x^{2*}) & f_2(x^{2*}) & \cdots & f_k(x^{2*}) \\ \vdots & \vdots & & \vdots \\ f_1(x^{k*}) & f_2(x^{k*}) & \cdots & f_k(x^{k*}) \end{pmatrix} \tag{8}$$

In the above payment matrix, define the minimum value of each column to be

$$f_i^{\min} = \min_{i=1,\dots,k} f_{ij}, i, j=1,\dots,k \tag{9}$$

The satisfaction level of each objective function $f_i$, $i=1,\dots,k$ objective function can be expressed in terms of the affiliation function as

$$\mu_{f_i(x)} = \frac{f_i(x) - f_i^{\min}}{f_i(x^{i*}) - f_i^{\min}} \tag{10}$$

The multi-objective planning model can be transformed into a fuzzy planning model as follows

$$\begin{cases} \max(\mu_{f_1(x)}, \mu_{f_2(x)}, \cdots, \mu_{f_k(x)}) \\ s.t. \quad x \in G \end{cases} \tag{11}$$

The payment matrix proposed by the above fuzzy compromise planning method not only considers the feasibility problem of feasible solutions in a single objective, but also considers the feasibility problem of feasible solutions in multiple objectives, e.g., a general mathematical planning model under constraints, using single-objective mathematical optimization methods to find the maximum and minimum values of each objective, and using a similar formula (10) to express the satisfaction function of the objective function. This method solves only locally considers a single objective without considering the intrinsic correlation relationship between the objectives, this paper considers the multiple objective optimization problem from a global viewpoint from the proposed method of payment matrix. The article defines the following global utility function:

$$M^{(\alpha)}(x) = \left(\sum_{i=1}^{k} w_i (\mu_{f_i(x)})^{\alpha}\right)^{1/\alpha}, \sum_{i=1}^{k} w_i = 1, 0 < |\alpha| < \infty \tag{12}$$

where $w_i, i=1,\dots,k$ represents the weight parameters of the considered objective function, which are evaluated and assigned to the objective function by the decision maker, e.g., using the eigenvalue approach in hierarchical analysis. Based on Eqs. (6)-(12), the fuzzy compromise planning model is expressed as follows:

$$\begin{cases} \max M^{(\alpha)}(x) = \left(\sum_{i=1}^{k} w_i (\mu_{f_i(x)})^{\alpha}\right)^{1/\alpha} \\ s.t. \quad x \in G \\ \qquad 0 < |\alpha| < \infty \\ \qquad \sum_{i=1}^{k} w_i = 1 \end{cases} \tag{13}$$

When $\alpha = 1$, model (13) is equivalent to the weight-addable model of fuzzy planning, i.e:

$$\begin{cases} \max M^{(1)}(x) = \left(\sum_{i=1}^{k} w_i \mu_{f_i(x)}\right) \\ s.t. \quad x \in G \\ \qquad \sum_{i=1}^{k} w_i = 1 \end{cases} \tag{14}$$

According to the form of the goal satisfaction sum, in addition, by expansion, when the goal weights are different, the form of the weighted satisfaction sum can be used. When $\alpha = -\infty$, the model (14) is equivalent to the weighted maximum-minimum model of fuzzy planning, which is equivalent to the fuzzy planning model at this time:

$$\begin{cases} \max M^{(-\infty)}(x) = \max \min \mu_{f_i(x)} / w_i \\ s.t. \quad x \in G \\ \qquad \sum_{i=1}^{k} w_i = 1 \end{cases} \tag{15}$$

The max-min algorithm can be extended to apply to a variety of optimization problems, linear or nonlinear, and in addition, the article gives a form for the product of the affiliation functions. In addition, taking into account the importance of each objective is not the same situation, the weighted max-min model form is given: the model focuses on considering the importance of all the objectives, the satisfaction of each objective is not too low, but often also makes part of the objectives are not fully optimized but this model is more complex, in this paper, the sports industry business operations do not need to use.

### *II. C.Principles of Decision Tree Algorithm*

Fuzzy compromise planning solves the problem of ambiguity in multi-objective optimization, but in the face of massive data and complex features, it still needs to rely on intelligent algorithms to further refine the decision-making process. The decision tree algorithm can effectively identify key influencing factors through information gain and Gini index optimization feature selection, provide technical support for classification management and risk prediction of sports industry projects, and thus realize the closed loop from theoretical model to data-driven decision-making.

Decision tree algorithm is divided into two types, discrete variables are commonly used in classification tree, common algorithms are ID3 (iterative dichotomous three generations) and C4.5 (contribution) algorithm, continuous variables are used in regression tree, common algorithms are CART (classification and regression) algorithm.

The key to decision tree generation is feature selection, i.e., selecting a feature as the splitting criterion of the node from the multiple features of the training set, the criterion of feature selection is that once the attribute is selected as the splitting criterion, the samples in the split nodes belong to the same category as far as possible, i.e., the node samples are at the highest purity, in order to measure the purity of the nodes, the article proposes the information entropy as a measure of the purity of the nodes of the decision tree.

Define the data set $D = \{d_1, d_2, \ldots, d_N\}$ as having $n$ samples, with the number of attribute values of the $k$ th class of samples $|y_k|$, and the proportion of samples of the $k$ th class in the set $D$ being $p_k$, then the information entropy of the data set $D$ is $Ent(D)$, see equation (16).

$$Ent(D) = -\sum_{k=1}^{|y|} p_k \log_2^{p_k} \tag{16}$$

The smaller value of entropy indicates the more uniformity and purity of the categories of the samples in the decision tree nodes. Assuming that Definition $Gain(D,a)$ is the information gain of attribute $a$ on dataset $D$, its calculation is shown in Equation (17).

$$Gain(D,a)=Ent(D)-\sum_{v=1}^{V}\frac{|D^v|}{|D|}Ent(D^v) \tag{17}$$

where $V$ is the number of possible values for attribute $a$ and $D^v$ is the number of samples with value $a^v$ for attribute $a$ in branch $V$. The decision tree formed by using "information gain" as a criterion for selecting the way of dividing attributes is called an iterative dichotomous three-generation decision tree, which is also known as an ID3 decision tree. In order to improve this shortcoming, the C4.5 (contribution) algorithm is proposed, which introduces the information gain rate as the criterion for feature selection. The biggest difference with ID3 is that C4.5 selects features with maximum information gain rate at each node.

Defining the information gain rate of feature $A$ as the ratio of the information gain of feature $A$ to its intrinsic value, the information gain rate of feature $A$, see equation (18).

$$Gain\_ratio(D,a)=\frac{Gain(D,a)}{IV(a)} \tag{18}$$

where the intrinsic value of the amount of information, see equation (19).

$$IV(a)=-\sum_{v=1}^{V}\frac{|D^v|}{|D|}\log_2\frac{|D^v|}{|D|} \tag{19}$$

Classification and regression problems are handled using the Classification and Regression Decision Tree Algorithm, or CART Decision Tree for short, which is one of the commonly used methods for constructing decision trees, which includes both classification and regression trees for both discrete and continuous data in a simple and efficient manner. The testing process produces a binary tree structure that is easy to understand and use. In the CART classification tree, the Gini index $Gini-index(D,a)$ for a feature indicates the purity of the sample set $D$ after dividing it with feature $a$ as the branch point, the Gini index is used to determine the split of the node, the Gini index measures the degree of confusion of the information, and the smaller the value indicates that the data is more ordered and the higher the certainty, which is calculated as follows:

Assuming that the set of samples $S=\{e_1,e_2,\ldots,e_N\}$, $N$ samples are categorized into $m$ classes, and the proportion of samples in class $i$ $C_i$ is $p_i=\frac{|C_i|}{N}(1\le i\le m)$, the \$Gini\$ index of set $S$ is defined, see equation (20).

$$Gini(S)=1-\sum_{i=1}^{m}p_i^2 \tag{20}$$

Let the cut point $T$ of attribute $A$ divide the sample set $S$ into two subsets $S_1$, $S_2$, then the cut point $T$ divides the Gini index definition of $S$, see equation (21).

$$Gini(A,T,S)=\frac{|S_1|}{|S|}Gini(S_1)+\frac{|S_2|}{|S|}Gini(S_2) \tag{21}$$

The cut point $T$ divides the $Gini$-gain of set $S$, see equation (22).

$$Gini(S,T,A)=Gini(S)-Gini(A,T,S) \tag{22}$$

Therefore, the CART algorithm is based on the principle of selecting the feature with the smallest Gini gain as the splitting node in order to increase the purity of the subset and ensure that the samples within the subset are more inclined to the same category. A kind of classification tree is created by dividing so that the leaf nodes of the final decision tree become leaf nodes for preventive maintenance versus other types of maintenance.

## III. Empirical Analysis of Business Operation in Sports Industry and Verification of Decision Support System

After completing the theoretical construction of the multi-objective optimization model of sports industry business operation, it is necessary to verify its decision support effectiveness through empirical analysis. This chapter integrates heterogeneous data collection from multiple sources, algorithm comparison experiments and system dynamics simulation to construct a complete analysis system covering the data base layer, model validation layer, and decision-making application layer, which provides empirical evidence for the selection of policy tools and optimization of business paths.

### *III. A. Characterization of the industry's revenue structure*

#### III. A. 1) Data acquisition

In this paper, the dataset is crawled through Python custom crawler technology to capture the sports industry related data from the public database of the State General Administration of Sports, the official websites of international sports organizations (e.g., the International Olympic Committee, the Asian Football Confederation), sporting goods sales platforms (e.g., Jingdong Sports, Tmall Sports Flagship Store), and sports event ticketing websites (e.g., Damai.com). Captured fields include the number of event participants, venue utilization rate, sporting goods sales, event broadcasting rights revenue, and sponsor investment.

#### III. A. 2) Scale and analysis of domestic sports industry revenue

According to industry reports and policy guidance, the revenue structure of commercial operations in the domestic sports industry can be categorized into six core areas, namely event revenue, sporting goods, sports training and education, sports tourism and health management, venue operation and leasing, and other derivative revenues.

Tournament-related revenues include tickets, broadcasting rights, advertising and sponsorship. Driven by the commercialization of e-sports, the introduction of international tournaments, technology-enabled viewing; sporting goods sales, including sports equipment, apparel, etc., in recent years, the rise of national wave brands, segmentation and track specialization; sports training and education, including youth training, fitness courses, mainly offline training institutions, while the online courses (such as Keep, private live) and the integration of sports and education policies to promote growth; sports tourism and health management such as Sports-themed tourism, rehabilitation services, is still an emerging field, but with consumer upgrading, people's health awareness, marathon event tourism, skiing vacations and recreation services demand surge; venue operation and leasing for public/commercial venue use; other derivative income including licensed merchandise, IP licensing, etc., focused on the periphery of the large-scale events, the market tends to be saturated, but the e-sports IP licensing has become a bright spot. Figure 3 shows the size of the total revenue share of the domestic sports industry in the six core sectors in 2024.

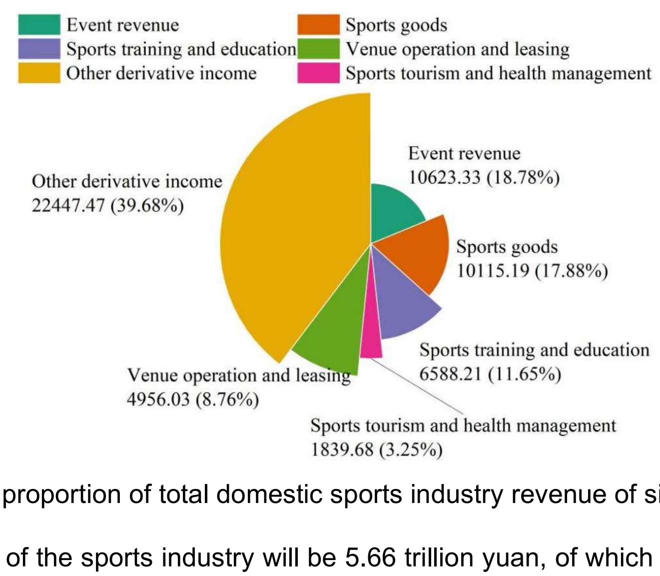


Figure 3: The proportion of total domestic sports industry revenue of six fields in 2024

In 2024, the total revenue of the sports industry will be 5.66 trillion yuan, of which “other derivative revenue” will become the largest segment with a 39.68% share (2,244.7 billion yuan), mainly due to the explosive growth of e-sports IP licenses, such as co-branded merchandise of “Glory of the King” and peripheral products of international tournaments. Revenue from traditional events accounted for 18.78% (1,062.3 billion yuan); sales of sporting goods accounted for 1,011.5 billion yuan, or 17.88%, driven by national wave brands such as Li-Ning and Anta, which remained stable; and venue operations accounted for 495.6 billion yuan, or 8.76%. The sports training sector accounted for 658.8 billion yuan, or 11.65%, benefiting from the “double-decrease” policy and the popularization of online courses, while sports tourism and health management accounted for 183.9 billion yuan, or 3.25%, with a small base and the potential of emerging areas not yet fully released.

Consolidate the six core areas into the following three categories: Event and IP-driven category: event-related revenues (tickets, broadcast rights, advertising and sponsorship) + other derivative revenues (licensed merchandise, IP licensing, etc.)

Physical products and facilities: sporting goods sales (sports equipment, apparel, etc.) + venue operation and leasing (public/commercial venue use)

Education and health services category: sports training and education (youth training, fitness programs) + sports tourism and health management (sports-themed tourism, rehabilitation services)

Figure 4 shows the revenue scale of the sports industry in various fields from 2015-2024.

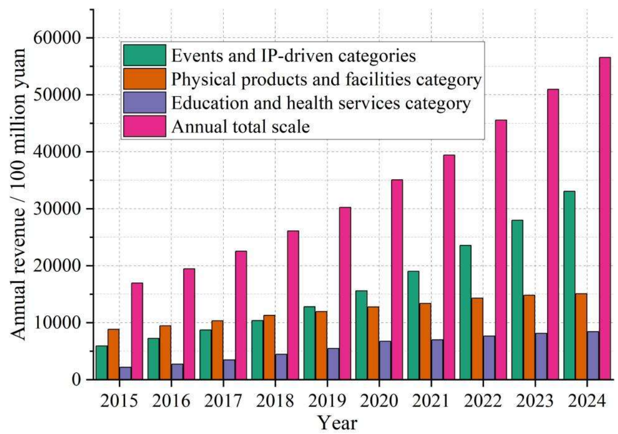


Figure 4: The revenue scale of various sports industries from 2015 to 2024

From the perspective of annual data, the three categories of revenue show the following characteristics: event and IP-driven revenue: revenue in 2015 was 592.3 billion yuan, and in 2024 it will increase to 3,307 billion yuan, with a compound annual growth rate of 21.3%, leading the whole industry. In 2022, revenue from the Winter Olympics jumped by 23.5% (2,358.8 billion yuan), and in 2024, the commercialization of esports and the launch of the League of Legends World Finals in China further boosted growth. Physical products and facilities: revenue in 2015 was 883.5 billion yuan, and in 2024 it will increase slightly to 1,507.1 billion yuan, with a compound annual growth rate of 6.1%, and the growth rate has slowed down significantly. From 2018 to 2020, it rebounded briefly due to the consumption of the "national tide", but after 2021, due to e-commerce competition and market saturation, the growth rate dropped to less than 2%. Education and health services: revenue of 219 billion yuan in 2015 will increase to 842.7 billion yuan in 2024, with a compound annual growth rate of 16.2%. After the implementation of the "double reduction" policy in 2021, sports training revenue increased by 40% year-on-year, while sports tourism recovered rapidly in 2023 after being hit by the epidemic, with revenue increasing by 18% year-on-year.

### *III. B. Linear Programming Model Validation and Application*

Based on the characteristics of the collected industrial basic data, the constructed linear programming model needs to be verified for algorithmic efficacy. This section evaluates the superiority of CART algorithm in multi-objective optimization scenarios of sports industry by designing comparative experiments of genetic algorithm and decision tree algorithm in terms of two dimensions, namely, operation efficiency and optimization accuracy.

#### III. B. 1) Experimental environment

Choose RAM 16 G, model Intel CORE i5 8th Gen core processor; choose 1 T for the size of the hard disk; training framework - Tensorflow, programming language - Python, graphics card NVIDIA Ge Force RTX 2060 SUPER, optimizer - Adam.

Linear Programming Classification and Regression Decision Tree Algorithm CART During crossover operation, the maximum crossover probability is set to 0.9, minimum crossover probability is set to 0.7, ordinary variance probability is set to 0.01, population size is set to 50, and the maximum value of number of iterations is set to 100.The static crossover probability and the variance probability in the CART algorithm are set to 0.8 and 0.01, respectively.

**III. B. 2) Algorithm testing results**

In order to verify the efficiency and accuracy of CART algorithm in multi-objective optimization of sports industry for resource allocation optimization and risk classification. Using the same experimental environment, four different linear programming algorithms, namely, traditional genetic algorithm, DPGA, ID3 and C4.5, as the experimental control group, are trained on the training set constructed in this study, and the average running time and the change of the fitness value in the training process are recorded to verify the effectiveness of the CART classification and regression algorithm proposed in this paper. The results of the comparison of the average running time of different algorithms are shown in Figure 5.

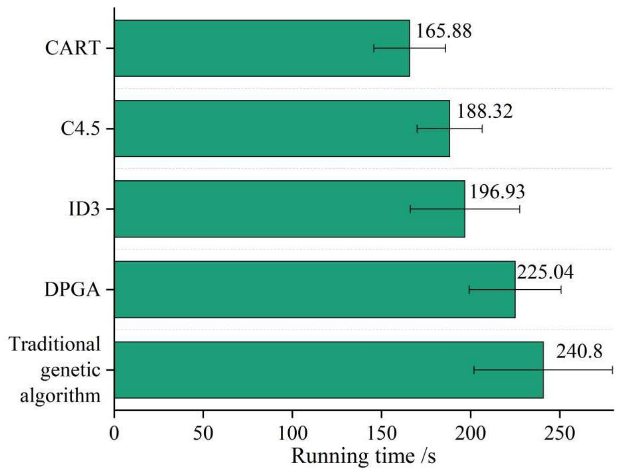


Figure 5: Comparison results of the average running time of different algorithms

Analyzing Figure 5, we can see that the average running time of the traditional genetic algorithm and DPGA algorithm is more than 200 s, which is slower, while the average running time of the decision tree algorithm ID3 and C4.5 is 196.93 and 188.32 s, respectively, and the average running time of the CART algorithm is 165.88 s, which is faster than that of the genetic algorithm and the DPGA algorithm by 74.92 and 59.16 s, respectively. 59.16s, indicating that the decision tree CART algorithm based on classification and regression significantly improves the algorithm operation speed.

The results of the comparison of the variation of the maximum adaptation of different algorithms are shown in Fig. 6.

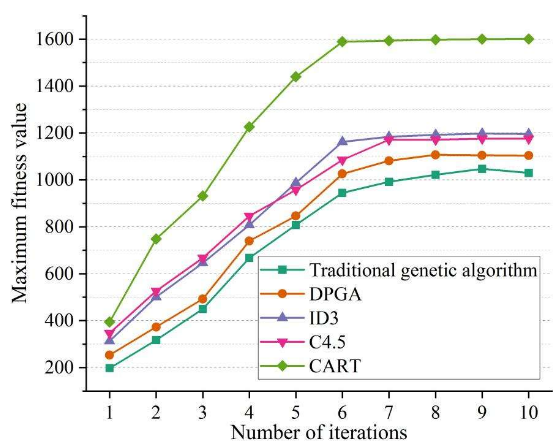


Figure 6: Comparison results of the maximum fitness changes of different algorithms

Analyzing Fig. 6 shows that the maximum fitness values of the five algorithms in the training process all become larger with the increase in the number of iterations, and gradually level off after reaching a certain number of times. However, the maximum fitness value of CART algorithm stabilizes at about 1600 after stabilization, which is higher than the other four algorithms by about 570.14, 496.15, 403.76 and 423.89, respectively, indicating that it has a better global search capability, higher algorithmic performance and efficiency, and a better quality of risk analysis and prioritization for sports industry projects.

### *III. C. Calibration of the Simulation Platform for Optimizing Business Operation Models in the Sports Industry*

After completing the efficacy verification at the algorithmic level, the optimization model needs to be embedded into the system simulation platform for application-level calibration. In this section, through model consistency test and sensitivity analysis of multiple policy variables, we quantify the marginal impact of policy tools such as financial support and tax incentives on the scale of industrial revenues, and construct a prototype of an interactive decision support system.

The calibration of the simulation platform for business operation optimization of sports industry based on linear programming model mainly contains model consistency test and model sensitivity analysis, which will be analyzed in the following.

#### III. C. 1) Model consistency test

Model consistency test is to compare the results of the model and historical data to test the interrelationships between the variables and whether they can be truly and effectively reflected in the operation of the model. Only if the model running results are true and effective, it can provide a reliable basis for policy analysis. Therefore, the model consistency test is necessary.

Table 1: Error estimation of output value of sports INDUSTRY-related indicators

| | Total revenue of the sports industry/100 million yuan | | | Revenue related to events/100 million yuan | | |
|---|---|---|---|---|---|---|
| | R | M | Error/% | R | M | Error/% |
| 2015 | 16948.14 | 16432.92 | 3.04 | 3440.44 | 3244.68 | 5.69 |
| 2016 | 19447.64 | 19216.21 | 1.19 | 3753.27 | 3716.49 | 0.98 |
| 2017 | 22540.63 | 22340.02 | 0.89 | 4012.12 | 3961.57 | 1.26 |
| 2018 | 26116.11 | 25638.19 | 1.83 | 5275.43 | 5008.49 | 5.06 |
| 2019 | 30225.59 | 29476.00 | 2.48 | 5954.32 | 5852.50 | 1.71 |
| 2020 | 35086.85 | 35034.22 | 0.15 | 7052.28 | 6343.53 | 10.05 |
| 2021 | 39414.84 | 39406.96 | 0.02 | 7449.24 | 7278.65 | 2.29 |
| 2022 | 45552.26 | 45438.38 | 0.25 | 9474.81 | 9394.27 | 0.85 |
| 2023 | 50971.88 | 50696.63 | 0.54 | 9225.75 | 9209.14 | 0.18 |
| 2024 | 56568.51 | 54690.44 | 3.32 | 10523.33 | 10482.29 | 0.39 |
| | Sales of sports goods/100 million yuan | | | Venue utilization rate/% | | |
| | R | M | Error/% | R | M | Error/% |
| 2015 | 2847.26 | 2836.44 | 0.38 | 46.85% | 45.23% | 3.45% |
| 2016 | 3519.90 | 3510.04 | 0.28 | 49.06% | 47.77% | 2.63% |
| 2017 | 4147.36 | 4112.52 | 0.84 | 53.96% | 50.37% | 6.65% |
| 2018 | 4335.25 | 4236.84 | 2.27 | 54.27% | 53.05% | 2.24% |
| 2019 | 5470.72 | 5340.52 | 2.38 | 52.53% | 49.99% | 4.83% |
| 2020 | 5964.62 | 5909.15 | 0.93 | 20.35% | 19.17% | 5.77% |
| 2021 | 7528.07 | 7356.43 | 2.28 | 32.74% | 32.60% | 0.42% |
| 2022 | 8745.98 | 8645.40 | 1.15 | 42.07% | 40.61% | 3.46% |
| 2023 | 9735.41 | 9705.23 | 0.31 | 54.95% | 54.57% | 0.69% |
| 2024 | 10115.19 | 10020.11 | 0.94 | 69.33% | 65.38% | 5.69% |

Based on the principle of comparability and accuracy of consistent test variables, in order to verify the reliability of the business operation model of the sports industry, the following indicators are selected: "total revenue of the sports industry (100 million yuan)" to reflect the overall market size; "Event-related revenue (100 million yuan)", including tickets, broadcast rights, and advertising sponsorship; "Sales of sporting goods (100 million yuan)": covering the sales of physical products such as sports equipment and apparel. and "Venue Utilization Rate (%)", which measures the operational efficiency of the venue for testing. The running results of the model are shown in Table 1, the interval of the consistency test is set to 2015-2024, and the absolute value of the relative error between the simulated value (M) and the real value (R) of each variable is within 10%, and the running results are real and valid, so the model is correct and can be used for business operation configuration analysis.

Table 1 shows the comparison and relative error of the simulated value (M) and the real value (R) of the four core indicators of the sports industry from 2015 to 2024, which verifies the consistency of the model. The error range of the total revenue of the sports industry is 0.02%~3.32%, with the smallest error of 0.15% in 2020 and the largest error of 3.32% in 2024, mainly due to the growth of emerging fields such as e-sports IP licensing exceeding expectations, and the model needs to be dynamically optimized. The error of event-related revenue is generally less than 6%, and the error in 2020 is only 10.05%, which may lead to the suspension of offline events due to the epidemic, and the model does not fully capture the compensation effect of online events. The error of sporting goods sales is stable at 0.31%~2.38%, reflecting the model's strong prediction ability for the real economy. The error range of the venue occupancy rate is 0.42%~6.65%, and the error of 5.77% in 2020 is due to the special impact of the closure of the venue during the epidemic.

### III. C. 2) Model sensitivity tests

The sensitivity analysis of system dynamics model in the commercial operation of sports industry is usually difficult to establish a strict quantitative expression, the main reason is that the model parameters (e.g., policy support strength, market preference, consumption trend) are often qualitative in nature, including the subjective judgment of the decision makers and fuzzy goals. The core objective of sensitivity analysis is to verify the degree of influence of policy control variables on the core development indicators of the sports industry.

In this study, the following four key policy variables are selected for simulation adjustment: the proportion of government financial support (as a share of total sports industry revenue), the rate of tax incentives (the proportion of income tax reduction and exemption for sports enterprises), the proportion of sponsor investment (the proportion of commercial cooperation funds in the total revenue of the event), and the proportion of sports science and technology R & D inputs (the proportion of R & D inputs in technologies such as intelligent venues, VR viewing, etc.). Based on the baseline value, the above variables are sequentially adjusted upward by 10%, 20% and 30%, and the effect of the policy adjustment is measured by the system level variable of the total revenue of the sports industry. The sensitivity analysis of the adjustment of the variables of the proportion of government financial support, tax preference rate, the proportion of sponsor investment, and the proportion of investment in sports science and technology R&D are shown in Figures 7, 8, 9, and 10, respectively.

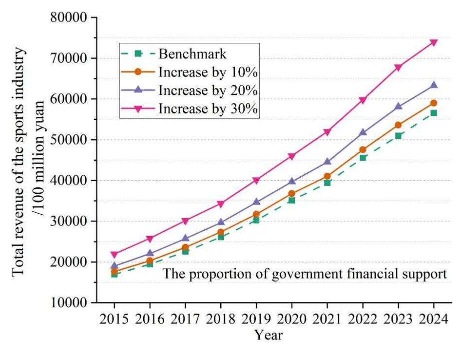


Figure 7: Sensitivity analysis of the proportion of government financial support

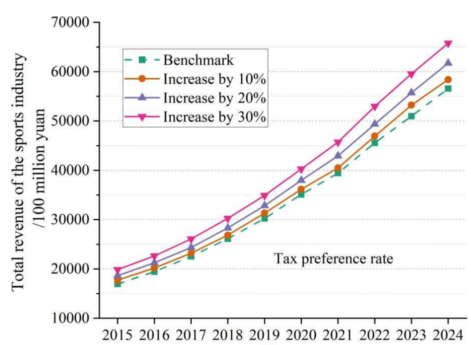


Figure 8: Sensitivity analysis of Tax Preference Rate Adjustment

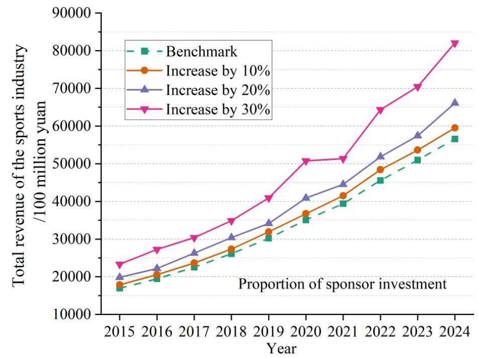


Figure 9: Sensitivity analysis of the Adjustment of sponsor Investment proportion

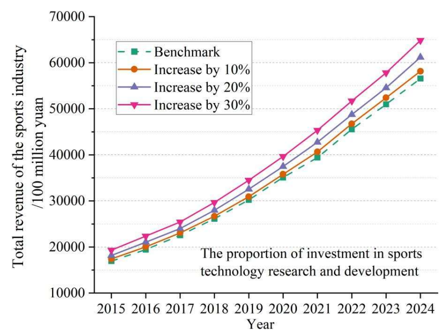


Figure 10: Sensitivity analysis of the Adjustment of the Proportion of R&D Investment

By adjusting four policy variables (government financial support, tax incentives, sponsor investment, and investment in science and technology R&D) and quantifying their impact on the total revenues of the sports industry, the following patterns are revealed. Percentage of government financial support: an upward adjustment of 30% leads to the largest increase in total revenues (from 5.66 trillion yuan to 7.40 trillion yuan in 2024, +30.8%), suggesting that financial support is the core leverage; Sponsor investment share: a 30% upward adjustment increases revenues to 8.20 trillion RMB in 2024 (+44.9%), reflecting the strong driving effect of business partnerships on the tournament economy; tax incentive rate and investment in science and technology R&D: lower sensitivity but significant long-term stacking effect (e.g., a 30% upward adjustment in tax incentives in 2024 pushes up revenues by 16.3%). The larger the upward adjustment of the policy variables, the gradual weakening of the pull effect of the unit increase on revenue. For example, when the proportion of government financial support is adjusted upward from 20% to 30%, the marginal benefit declines as revenue growth drops from 11.9% to 16.9% in 2024.

## IV. Commercial Operation and Development Path of Sports Industry

Driven by both digital economy and policy dividend, China's sports industry has ushered in a period of rapid development, but it also faces the challenges of conflicting goals, inefficient resource allocation and Internet transformation. Based on the linear planning model, intelligent algorithm and Internet integration perspective, the following development path is proposed.

### *IV. A. Technology-driven: building a data-driven decision support system*

Application of multi-objective optimization model: Using linear programming and fuzzy compromise planning, quantify the weights of economic benefits such as income growth rate and social benefits such as employment rate, and balance the conflicting objectives through payment matrix and global utility function. Combining CART decision tree algorithm to optimize feature selection and improve the efficiency of risk classification and prioritization.

Dynamic simulation and policy modeling: An interactive simulation platform is established to support the government and enterprises in dynamically adjusting variables such as financial support and tax incentives, and predicting the marginal effects of policies.

### *IV. B. Internet convergence: innovative business models and formats*

Online and offline synergistic operation: retaining the service advantages of brick-and-mortar stores (such as experiential consumption), while expanding e-commerce platforms and social media marketing, and utilizing big data to analyze user preferences. For example, e-sports IP licensing revenue accounted for 39.68% in 2024, and it is necessary to strengthen the development of online derivatives such as live broadcast of tournaments and virtual goods.

Layout of emerging fields: Focus on the development of sports tourism, health management and other light asset fields, combining VR/AR technology to create an immersive viewing experience, and tapping into the potential of marathon, skiing and other themed tourism.

### *IV. C. Policy and capital synergies: strengthening leverage*

Optimization of fiscal and tax tools: the government needs to refine the Internet sports industry support policies, such as targeted subsidies for smart arena construction and additional deduction for R&D expenses, etc., which will have a significant long-term stacking effect.

Introduction of social capital: Encourage enterprises to participate in the operation of events through sponsorship and naming, and establish a risk-sharing mechanism.

### *IV. D. Talent and Organization Building: Strengthening the Roots of Development*

Cultivation of Composite Talents: Joint colleges and universities offer “Sports + Data Science” cross-curricula to strengthen the application of algorithms and Internet operation capabilities; enterprises establish incentive mechanisms to attract technical talents.

Standardized management system: Referring to international experience (e.g. NBA digital operation), build a standardized process covering data collection, model iteration and risk monitoring to reduce the cost of trial and error.

The sports industry needs to take data intelligence as the core, the Internet as the link, and policy and capital as the support to form a closed loop of “technology empowerment - model innovation - ecological synergy”. In the future, we should focus on the incremental market such as e-sports and health services, strengthen the global resource allocation ability, and promote the industry to move toward the trillion scale.

## V. Conclusion

In this study, a multi-objective optimization model for commercial operation of sports industry is constructed by integrating linear programming, fuzzy compromise planning and decision tree algorithm. Experimental validation shows that the CART algorithm significantly outperforms the traditional method in terms of running efficiency of 165.88 seconds and optimization accuracy of maximum fitness value of 1600, which provides an efficient tool for project prioritization and risk prediction. The model consistency test based on real data from 2015-2024 shows that the simulation error of total revenue of sports industry is lower than 3.32%, and the error of venue utilization rate is stable at 0.42%-6.65%, which confirms the reliability of the model. The sensitivity analysis further reveals the influence law of policy variables: the marginal effect of government financial support and sponsor investment on revenue growth is significant, raising 30.8% and 44.9%, respectively, while the long-term superimposed effect of tax incentives and science and technology research and development investment should not be ignored. The results of the study can provide a quantitative basis for government departments to optimize financial support strategies and enterprises to formulate business cooperation plans, and also provide theoretical support for emerging areas such as e-sports IP licensing and sports tourism potential exploration.

## References


[1] Leonov, Y. (2020). Current trends in the sports industry and their influence on the development of organizations. Economics, Finance and Management Review, (4), 89-96.

[2] Li, C., Li, D., & Huang, C. (2024). Innovations in Sports Industry: Trends and Transformations. Psychology of Sport & Exercise, 75, 112416.

[3] Orunbayev, A. (2023). Globalization and sports industry. American Journal Of Social Sciences And Humanity Research, 3(11), 164-182.

[4] Güvercin, A., & Mil, H. İ. (2016). The factors that affect the development of sports industry as an economy. International Journal of Sport Culture and Science, 4(Special Issue 2), 515-521.

[5] Liu, D., Zhang, J. J., & Desbordes, M. (2017). Sport business in China: Current state and prospect. International journal of sports marketing and sponsorship, 18(1), 2-10.

[6] Kharchenko, T. O., & Ziming, L. (2021). The Relationship between Sports Industry Development and Economic Growth in China. Accounting & Finance/Oblik i Finansi, (91).

[7] Wu, C. (2024). The Impact of Sports Industry Output on Economic Growth: Evidence from China. Journal of the Knowledge Economy, 1-21.

[8] Gholamian, J., Ramezanzade, M., Mahmoudi, A., & Azizi, B. (2023). Success in the process of sports businesses. Journal of Strategic Management Studies, 14(55), 191-208.

[9] Wang, Y. (2021, December). Study on the Operating Model of Sports Industry Under COVID-19. In 2021 4th International Conference on Humanities Education and Social Sciences (ICHESS 2021) (pp. 1154-1163). Atlantis Press.

[10] Paul, A. K. (2023). Future of sports operations and sports event management in uncertain environment: a critical review. Sports Management in an Uncertain Environment, 189-218.

[11] Ziming, L., & Kharchenko, T. O. (2021). Research on the Development Path of Sports Industry in the Context of Belt and Road. Turkish Journal of Computer and Mathematics Education, 12(14), 3780-3783.

[12] Pittz, T., Bendickson, J. S., Cowden, B. J., & Davis, P. E. (2021). Sport business models: a stakeholder optimization approach. Journal of Small Business and Enterprise Development, 28(1), 134-147.

[13] Shi, Y., Song, Q., & Li, L. (2024). Research on the factors and path of sports industry development in China: A fsQCA study of 31 provinces. Plos one, 19(4), e0298167.

[14] Dyer, M., Gärtner, B., Megiddo, N., & Welzl, E. (2017). Linear programming. In Handbook of discrete and computational geometry (pp. 1291-1309). Chapman and Hall/CRC.

[15] Kalwar, M. A., Khan, M. A., Shahzad, M. F., Wadho, M. H., & Marri, H. B. (2022). Development of linear programming model for optimization of product mix and maximization of profit: case of leather industry. Journal of Applied Research in Technology & Engineering, 3(1), 67-78.

[16] Donkor, L., Essien, E., & Affrifah, N. S. (2023). A Systematic Review of Linear Programming Techniques as Applied to Diet Optimisation and Opportunities for Improvement. Journal of Optimization, 2023(1), 1271115.

[17] Sajadi, S. M., Baghaie, S., & Rezaei, R. (2024). Optimizing sports development: Identifying and prioritizing key indicators for professional and competitive sports. World Development, 180, 106651.