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Decision Support for Feasibility Evaluation of Ecology-Oriented Development Projects: Integrating Case-Based Reasoning and Machine Learning Approaches

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Abstract

Ecology-oriented development (EOD) projects integrate ecological governance with revenue-generating industries, but their financial feasibility evaluation and resource balancing depend heavily on expert judgment. This study develops a decision-support method combining case-based reasoning (CBR) and machine learning (ML) to support the systematic reuse of historical project experience. A standardized case representation framework and an EOD case database were established. Gradient boosting decision trees (GBDT) were then used to determine predictive-importance weights, support weighted similarity calculation, and predict key financial indicators, while CBR linked retrieved case information to project-specific recommendations through experience transfer and adaptation. The method was applied to the Xibei Canal EOD project in Wuxi, China. The three most similar historical cases achieved similarities of 91.02%, 90.26%, and 89.52%, respectively, providing complementary references for financing arrangements and industrial cross-subsidization of the Xibei Canal EOD project. GBDT achieved R^2 values of approximately 0.87, 0.97, 0.93, and 0.97 for predicting financial internal rate of return (FIRR), financial net present value (FNPV), payback time (Pt), and debt service coverage ratio (DSCR), respectively, providing quantitative support for scheme evaluation. Threshold sensitivity analysis further clarified the scope of reuse-eligible cases and the corresponding adaptation requirements under different screening conditions. The proposed method provides structured, quantitative, and traceable support for EOD project screening, preliminary financial assessment, resource balancing, and scheme comparison.

Keywords: ecology-oriented development (EOD) project; case-based reasoning (CBR); machine learning (ML); financial feasibility; resource balancing; decision support

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1. Introduction

Ecology-Oriented Development (EOD) projects have emerged as an innovative implementation model for addressing the limited profitability and financing constraints of traditional environmental governance projects [1–3]. By integrating ecological restoration, environmental infrastructure, and revenue-generating industries within a unified project

system, the EOD model seeks to transform ecological resources into sustainable economic value [4]. It combines public-benefit environmental governance activities with associated industries that have stronger revenue-generating potential through industrial chain extension, bundled development, and integrated implementation [5]. In this model, local governments generally provide overall coordination, while project companies undertake integrated investment, construction, and operation [6]. Revenues generated from associated industries are then used to support ecological investment and long-term environmental governance, thereby promoting the internalization of ecological value and the coordinated development of environmental and economic objectives [7].

Compared with traditional publicly funded ecological projects, EOD projects introduce a more complex coupling of environmental objectives (e.g., ecological restoration), resource balancing, financing structures, regional fiscal conditions, and project financial performance [8]. Here, resource balancing refers to the identification and configuration of revenue-generating industries or operational resources whose cash flows can compensate for the investment and operating costs of public-benefit ecological governance activities and support the overall financial balance of the project. Typical resource balancing includes eco-agriculture, cultural tourism, and district development [9,10]. Resource balancing is therefore closely linked to financial feasibility evaluation, which assesses whether the scale, timing, and stability of the revenues generated by these resources are sufficient to support project profitability, investment recovery, and debt-servicing capacity [4,7].

Since environmental governance projects usually have strong positive externalities but limited direct profitability, the EOD model relies on the development of such resource balancing to support ecological investment and promote the resolution of environmental problems. The effectiveness of resource balancing is therefore reflected in financial indicators, making financial feasibility evaluation and resource balancing analysis decisive during the planning stage; however, these tasks still rely heavily on expert judgment and ad hoc case references [11]. This experience-driven decision process lacks support from systematic and quantitative scientific models, making it difficult to fully justify the rationality and preliminary financial feasibility of project portfolio schemes. As a result, the objectivity and accuracy of financial risk assessment and resource carrying-capacity analysis remain insufficient, which may create potential uncertainties for subsequent financing, implementation, and long-term operation. Systematic methods that are both computationally tractable and transferable across projects have not been established [12].

Previous studies have provided important foundations for understanding the implementation logic and decision-making difficulties of EOD projects. For example, Xie et al. [13] examined ecological value capture pathways under the EOD model. Wang et al. [14] discussed the cooperation mechanism between Public–Private Partnership (PPP) and EOD. Li et al. [4] summarized the case characteristics and design logic of EOD practices in China. Feng et al. [15] and Xia et al. [16] further analyzed public–private cooperation, incentive mechanisms, and stakeholder behavior in ecological restoration and rural environmental governance projects. These studies have deepened the understanding of institutional arrangements, ecological value realization, and private participation in EOD projects. However, most of them focused on policy interpretation, mechanism analysis, and qualitative case discussion, and only limited attention has been paid to the financial feasibility aspects of EOD projects [17]. Financial feasibility and resource balancing at the planning stage are critical for the subsequent implementation of EOD projects because ecological governance activities usually generate strong positive externalities but face inherent difficulties in internalizing returns through market-based financing [18]. Therefore, associated industries must be introduced as a resource balancing mechanism to compensate for public-benefit environmental governance investment through operating revenues. In this process, financial indicators such as Financial Internal Rate of Return (*FIRR*), Financial

Net Present Value (*FNPV*), and Debt Service Coverage Ratio (*DSCR*) provide the core basis for evaluating the preliminary financial feasibility, investment-recovery characteristics, and debt-servicing capacity of EOD projects. For project-level financial feasibility evaluation and resource balancing, traditional approaches still rely mainly on expert judgment, financial estimation templates, and references to a limited number of comparable cases [1,4,5].

To address these limitations, this study proposes a decision-support method for the financial feasibility evaluation and resource balancing of EOD projects by integrating case-based reasoning (CBR) [19] and machine learning (ML). The method combines historical experience reuse with data-driven financial prediction. First, a standardized case representation framework and an EOD case database are established using a triple structure comprising case identification, problem description and solution. Second, heterogeneous case data are classified and processed, and a gradient boosting decision tree (GBDT) model [20] is employed to predict key financial indicators to support investment and financing decisions, while CBR, informed by GBDT-derived feature-importance weights, is used to retrieve similar cases and formulate project-specific strategies. Third, retrieved case information is linked to project-specific recommendations through experience transfer and adaptation, with differences in financing structures informing alternative financing scenarios. The framework is illustrated through the Xibei Canal EOD project in Wuxi, China, demonstrating comparable-case retrieval, financing and resource-balancing recommendations, and the prediction of *FIRR*, *FNPV*, *Pt*, and *DSCR*. Sensitivity analysis further examines how similarity thresholds affect experience-reuse eligibility and adaptation requirements. The main contribution is an integrated CBR-ML framework that connects standardized case representation, predictive-importance weighting, and financial prediction with traceable experience transfer. By explicitly linking recommendations to information extracted from individual cases, the method provides structured and quantitative support for EOD project planning, screening, preliminary financial appraisal, and resource-balancing scheme comparison.

The remainder of this paper is organized as follows. Section 2 reviews research on EOD projects, CBR, and ML-based engineering decision-making and identifies the research gaps. Section 3 presents the methodology, including case representation, data processing, similarity calculation, experience reuse, and financial indicator prediction. Section 4 illustrates the application to the Xibei Canal EOD project, linking retrieved case information to financing and resource-balancing recommendations and comparing financial predictions with project appraisal estimates. Section 5 presents the financial-input sensitivity and scenario-based response-surface analyses, examines the effects of similarity thresholds on case retrieval, and discusses theoretical and practical implications. Section 6 summarizes the main findings and outlines future research directions.

2. Literature Review

2.1. EOD Financial Feasibility and Resource Balancing

EOD projects have attracted considerable attention because they integrate ecological and environmental governance with revenue-generating industrial development. Existing studies have mainly examined the conceptual framework, policy logic, implementation pathways, institutional constraints, and risk allocation of the EOD model [1,8]. From the perspective of ecological value realization, Xie et al. [13] analyzed value-capture pathways for different types of EOD projects, while Wang et al. [14] discussed the integration of public–private partnerships with EOD implementation. Other studies [1,15,21] have examined social-capital participation, stakeholder incentives, cooperation mechanisms,

and the effects of institutional arrangements on project investment and revenue structures. These studies provide an important basis for understanding how ecological benefits may be linked with industrial development and market-oriented implementation.

Financial feasibility and resource balancing are central to this implementation logic. Ecological governance activities usually generate substantial public and environmental benefits but limited direct cash flows, making it difficult to recover investment through conventional market mechanisms [15,16]. EOD projects therefore introduce revenue-generating resources, such as eco-agriculture, cultural tourism, and district development, to compensate for ecological governance costs and support long-term project operation [4,22]. The financial sustainability of this arrangement depends on whether the scale, timing, and stability of the revenues generated by these resources are sufficient to support profitability, investment recovery, and debt servicing. Existing studies [1,21,23] have considered financing structures, ecological value realization, public–private cooperation, and risk-sharing mechanisms. However, most analyses remained at the policy, institutional, or program level and provided limited quantitative support for evaluating project-level resource portfolios and financial outcomes.

Although EOD is primarily introduced as a policy and implementation model in China, related international research on ecological restoration finance, green infrastructure investment, nature-based solutions, and ecosystem-service financing has addressed similar challenges. These studies [24,25] indicate that ecological projects frequently involve high initial investment, long payback periods, uncertain revenue streams, and difficulties in monetizing positive environmental externalities. Their financial sustainability therefore depends on coordinated financing structures, revenue-generating activities, risk allocation, and long-term cash-flow management. Nevertheless, they rarely transform historical ecological project experience into standardized and reusable decision knowledge. The consequence is that a project-level framework capable of jointly considering environmental problems, resource balancing modes, financing conditions, regional capacity, and financial performance remains lacking.

2.2. CBR and ML for Engineering Decision Support

CBR and ML have been widely applied to engineering problems involving limited information, contextual heterogeneity, and complex relationships among decision variables. CBR retrieves historical cases that are similar to a target problem and adapts their solutions, making it suitable for cost estimation, risk assessment, project planning, and design decision-making [23,26]. ML methods complement this experience-reuse mechanism by identifying feature importance, learning nonlinear relationships, and predicting project outcomes from historical data. Previous construction studies [27,28] have applied regression, neural networks, support vector machines, random forests, and CBR to bid/no-bid decisions, cost estimation, schedule-cost trade-offs, and project-risk prediction.

Recent studies have extended these applications by integrating case knowledge with data-driven learning. Li et al. [29] developed a data-driven and explainable CBR method for financial-risk detection, in which feature-scoring and optimization techniques were used to reduce dependence on manually assigned similarity parameters. Their findings demonstrate that data-driven CBR can combine predictive performance with traceable case-based explanations. Li et al. [19] further reviewed CBR applications in building-retrofit decision-making and identified case representation, similarity attributes, weighting methods, and adaptation mechanisms as key determinants of decision quality. These recent developments indicate that CBR and ML have complementary strengths. Specifically, CBR preserves contextual experience and provides interpretable case evidence, whereas ML offers objective feature weighting and nonlinear prediction capabilities [30,31].

However, the direct application of existing CBR or ML methods to EOD projects remains difficult. Conventional CBR often relies on manually defined feature weights and similarity functions, which may introduce subjectivity when cases contain mixed numerical, categorical, and Boolean information [32]. Pure ML models, by contrast, can produce quantitative predictions but do not directly retrieve transferable implementation experience or explain how historical project schemes can inform a new project [33]. These limitations are particularly relevant to EOD projects because their financial performance is jointly affected by environmental problem types, resource balancing portfolios, financing arrangements, and regional fiscal conditions. This requires a method that can link interpretable historical experience reuse with data-driven weighting and financial prediction.

Overall, three gaps can be identified. First, existing EOD studies mainly focus on policy interpretation, implementation mechanisms, and qualitative case analysis, while standardized and computable representations of project-level financial feasibility and resource balancing remain insufficient. Second, research on ecological project financing and financial sustainability rarely converts heterogeneous historical cases into structured knowledge that can be retrieved, compared, and adapted for new projects. Third, although recent CBR and ML studies have improved case retrieval, feature weighting, prediction, and interpretability, an integrated framework linking EOD case representation, objective similarity weighting, experience reuse, and financial indicator prediction has not yet been established. To address these gaps, this study integrates CBR with GBDT-based learning to organize heterogeneous EOD information into standardized cases, identify the predictive importance of project attributes, retrieve relevant historical experience, and provide quantitative support for financial feasibility evaluation and resource balancing scheme comparison.

3. Methodology

This study develops a decision-support method for evaluating the financial feasibility and resource balancing of EOD projects by integrating CBR and ML. Figure 1 presents the overall workflow, from case representation and data processing to case retrieval, revision, recommendation, case optimization, and financial indicator prediction. An initial case base containing 126 national and provincial pilot projects is organized according to case identification (ID), problem description (P), and solution information (S). For a new target project, input information is standardized using the same structure, and CBR retrieves the three most similar historical cases using GBDT-derived predictive-importance weights. The retrieved similarities are then assessed against thresholds of 60% and 85%. If the similarity requirement of 60% is not met, the system indicates insufficient comparable experience and a ‘defer’ decision is made. Cases meeting the 60% threshold but falling below 85% require refinement of the input parameters (i.e., ID, P, and S) before further evaluation. When the 85% requirement is satisfied, the new target project can proceed to use the retrieved cases to provide implementation references and enter the trained GBDT model for the prediction of financial indicators. These predictions support subsequent scheme comparison and multi-objective optimization involving key parameters, including total investment and GDP. The workflow combines comparable case experience with financial predictions and optimization results to support project implementation decisions.

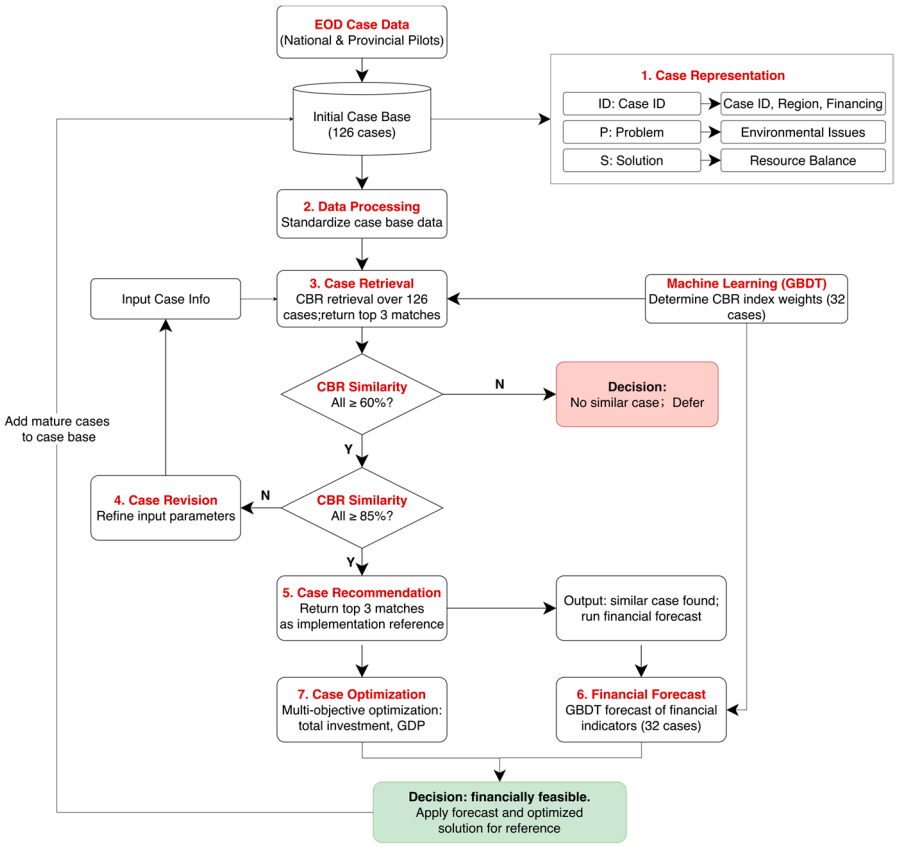


Figure 1. Architecture of the proposed model.

3.1. EOD Project Case Representation

Case representation constitutes the foundation of the proposed decision-making method. Following the problem-solution logic of CBR, a triple structure, $C = (ID, P, S)$, is proposed to standardize EOD project descriptions. Specifically, ID ensures case identification and traceability by recording basic project information, financing structure, and regional fiscal conditions, including project number, project name, implementing entity, location, total investment, equity capital, loan amount, loan term, GDP, fiscal revenue, government debt, and debt ratio. *P* defines the decision context by describing the environmental problems addressed, including water, air, soil, marine, agricultural and rural pollution control, solid waste treatment, and ecological restoration. *S* records the resource balancing or industrial modes adopted to support ecological governance investment, such as ecological agriculture, cultural tourism, ecological health care, resource utilization, ecological industry, industrial feedback, and district development. Accordingly, the triple structure establishes a logical connection among project conditions, environmental problems and balancing solutions, thereby supporting case retrieval, scheme reuse and similarity calculation.

The case base was developed through the research team's EOD project practice and comprises national-level pilot and demonstration projects and provincial-level pilot projects. The former includes EOD projects approved or jointly announced by the Ministry of Ecology and Environment, the National Development and Reform Commission, the China Development Bank, and other relevant authorities. The latter includes provincial-level EOD pilot projects organized and implemented in Anhui, Zhejiang, Fujian, Jiangsu, Shandong, and other provinces. Source materials primarily included official project lists, government disclosures, project implementation plans, feasibility study reports, financing documents, and other publicly available project materials. Inclusion required an identifi-

able project name, location, and implementing entity; a clearly defined ecological and environmental governance objective; an identifiable resource balancing mode; and sufficient investment, financing, and regional fiscal information to support standardized case representation. These criteria ensured that each retained project could be represented across three dimensions: case identification, problem description, and solution.

During data screening, duplicate records were identified and removed by cross-checking project names, locations, implementing entities, approval information, and investment scales. Projects were excluded if their identity or EOD status could not be verified, discrepancies in key information across sources remained unresolved after cross-checking, or core variables required for case retrieval were unavailable. For partially incomplete records, missing information was supplemented, where possible, by cross-referencing official government documents, project reports, financing materials, and regional statistical data. Records with unresolved missing values in key input variables were excluded from the corresponding retrieval analysis. As all projects were located in China, monetary information was originally reported in RMB. Before analysis, total investment, equity capital, loan amounts, regional GDP, fiscal revenue, and government debt were converted into consistent monetary units, while percentage and time-related indicators were harmonized according to their original definitions. Numerical variables were subsequently normalized to reduce the influence of differences in measurement units and magnitude. Following compilation, verification, screening, and standardized coding, 126 valid EOD project cases were retained. The resulting case base covers multiple environmental problem types, resource balancing modes, financing structures, and regional conditions, providing a diverse empirical basis for the CBR analysis.

3.2. Data Processing and GBDT-Based Weight Calculation

The case data of EOD projects are characterized by mixed data types, diverse dimensions, and inconsistent measurement units [34]. It is necessary to systematically process the raw data before conducting case retrieval and model prediction. Considering the aforementioned case triple structure, this study classifies the core fields in the case base into five types: string, symbolic, float, integer, and Boolean. This classification enhances the effectiveness of subsequent similarity calculation and model training. Through this classification, the original case data are transformed from a heterogeneous information set into structured inputs suitable for a unified computational framework.

Table 1 presents the data type classification of the core fields in the EOD project case base. String-type fields are used to record basic textual information. Symbol-type fields describe discrete locational attributes. Float-type fields cover continuous numerical variables. Integer-type fields are used to record loan terms, while Boolean-type fields indicate whether specific environmental problems and resource balancing are involved. This classification reflects the mixed data structure of EOD project cases and provides a basis for applying differentiated processing methods to different types of fields.

Table 1. Data types of EOD project cases.

Data Type	Covered Fields
String	Project ID, project name, implementing entity
Symbol	Project location, including province and prefecture-level city
Float	Total investment, equity capital, loan amount, regional gross domestic product, fiscal revenue, government debt, government debt ratio
Integer	Loan term
Boolean	Environmental problems, balancing resourcing

After completing the data classification, supervised learning methods are employed to identify indicator weights and support subsequent weighted similarity calculation. Considering that the financial performance of EOD projects is jointly affected by investment scale, financing structure, regional fiscal conditions, environmental governance types, and resource balancing modes, 23 indicators are selected as input variables, including total investment, equity capital, loan amount, loan term, regional GDP, fiscal revenue, government debt, government debt ratio, air pollution prevention and control, water ecological environment protection, comprehensive governance of key sea areas, soil pollution prevention and control, agricultural and rural pollution control, solid waste treatment and disposal and comprehensive resource utilization, ecological protection and restoration, other environmental governance, ecological agriculture, cultural tourism, ecological health and wellness, resource utilization, ecological industry, industrial feedback, and district development. Four project performance-related indicators are used as output variables, namely *FIRR*, *FNPV*, *Pt*, and *DSCR*. Four commonly used models, namely support vector machine (SVM) [35], random forest (RF) [36], linear regression (LR) [37], and GBDT [38], are selected for comparative training. The coefficient of determination R^2 is adopted as the evaluation metric to assess the fitting performance of different models for each output indicator.

To ensure the consistency and reproducibility of the model comparison, SVM, RF, LR, and GBDT were implemented in Python 3.8 and trained via 32 EOD project cases with the most complete information (i.e., those that contain both the input and output variables mentioned above). This is feasible as previous research indicates that small datasets can support exploratory machine learning studies when appropriate validation procedures are applied [39]. Five-fold cross-validation was adopted for model training and performance evaluation. Numerical variables were standardized using the mean and standard deviation calculated from the training folds, and the fitted transformation was then applied to the corresponding validation fold to prevent data leakage. The SVM model employed a radial basis function kernel, with the penalty parameters C, γ, and ε set to 10, 0.1, and 0.1, respectively [40]. The RF model consisted of 200 decision trees, with a maximum tree depth of 10, a minimum of two samples required to split an internal node, a minimum leaf size of one, and the square root of the total number of predictors considered at each split. The LR model was estimated using ordinary least squares with an intercept after predictor standardization. The GBDT model contained 200 regression trees, with a learning rate of 0.05, a maximum tree depth of 3, a minimum of two samples required to split an internal node, a minimum leaf size of one, and a subsampling ratio of 0.8. The squared-error loss function was adopted for model optimization.

Figure 2 presents the R^2 values of the four models for *FIRR*, *FNPV*, *Pt*, and *DSCR*. LR generally achieves lower R^2 values than the other models, while SVM and RF perform relatively well for some indicators, but their predictive performance varies across the four outputs. In comparison, the GBDT model jointly predicts the four financial indicators by minimizing the average squared error across their standardized values, achieving higher overall R^2 performance across the evaluated indicators.

To further ensure the model stability, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were analyzed to assess the variation in prediction errors [41]. As shown in Figure 3, GBDT achieved the lowest MAE and RMSE for FNPV and DSCR, with values of approximately 4200 and 4800 for FNPV and 0.030 and 0.034 for DSCR, respectively. The relatively narrow error bars for these two indicators indicate limited variation across cross-validation folds. For FIRR, GBDT yielded an MAE of approximately 0.011 and an RMSE of 0.013, comparable to RF but slightly higher than SVM. For Pt, its MAE and RMSE were approximately 0.95 and 1.10, respectively, close to those of RF and lower

than those of SVM and LR. Overall, GBDT demonstrated favorable predictive performance across the four indicators, with particularly low errors and consistent performance for FNPV and DSCR.

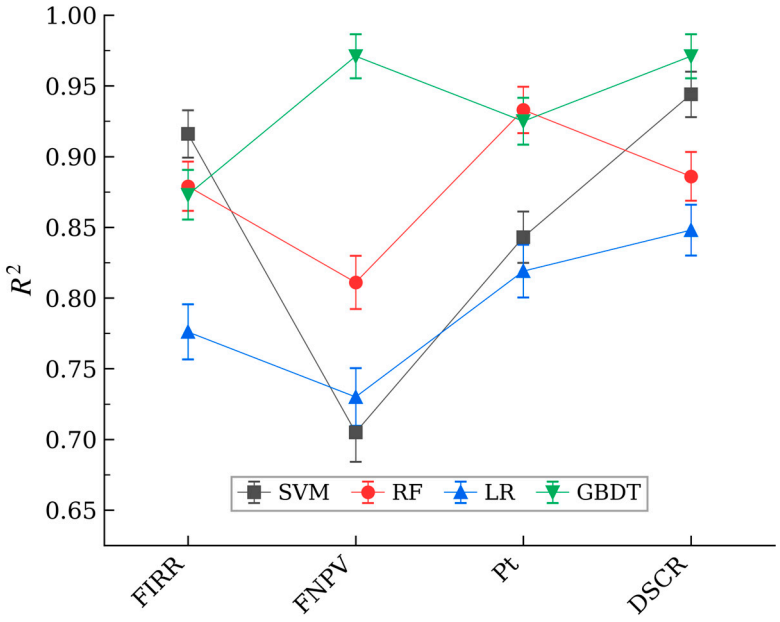


Figure 2. Five-fold cross-validated R^2 values of the four models.

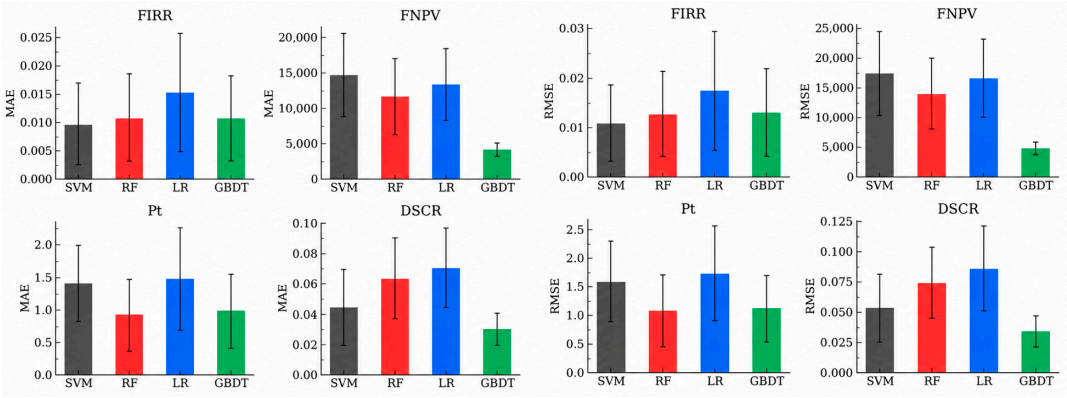


Figure 3. Comparison of MAE and RMSE across the four financial indicators.

Together, these results (Figures 2 and 3) support the selection of GBDT as the unified model for financial indicator prediction. Within the same trained multi-output model, predictor importance is quantified by each input variable's cumulative contribution to reducing the joint prediction loss across the four standardized financial outcomes. These importance scores are then normalized and used as indicator weights in the subsequent similarity calculation, giving greater weight to project characteristics that contribute more to predicting financial performance. Thus, financial prediction and indicator weight identification are linked through the same model and learning objective. The resulting weights represent predictive importance rather than causal effects.

For each input indicator x_j, the GBDT model evaluates its contribution according to the cumulative reduction in prediction error across all regression trees. The raw importance score of indicator x_j can be expressed as [42]:

$$I_j = \sum_{m=1}^{M} \sum_{t \in T_m} \Delta L_{m,t} \cdot E(v_{m,t} = x_j) \tag{1}$$

where M denotes the number of regression trees, T_m represents the set of internal splitting nodes in the m-th tree, $\Delta L_{m,t}$ is the loss reduction produced by node t, and $E(v_{m,t} = x_j)$ is an indicator function that equals 1 when indicator x_j is used for splitting at node t. To make the feature contributions comparable, the raw importance scores are normalized as follows [42]:

$$\omega_j = \frac{I_j}{\sum_{j=1}^{n} I_j} \tag{2}$$

where ω_j is the normalized weight of indicator x_j, and n is the total number of evaluation indicators. These normalized weights are further used to synthesize the global similarity between the target case and historical cases [38]:

$$S(C_0, C_i) = \sum_{j=1}^{n} \omega_j \cdot s_j(C_0, C_i) \tag{3}$$

where $S(C_0, C_i)$ denotes the global similarity between the target case C_0 and the historical case C_i, and $s_j(C_0, C_i)$ represents the local similarity of the two cases on indicator x_j.

The data processing and indicator weight identification procedures provided a unified data foundation and weighting support for the subsequent calculation of global similarity in case retrieval and the prediction of financial indicators. In this study, a unified multi-output GBDT model was developed to simultaneously predict *FIRR*, *FNPV*, *Pt*, and *DSCR*. Because the four outcomes had different units and numerical scales, each outcome was standardized before model training to prevent variables with larger magnitudes from dominating the loss function. The joint loss of the multi-output model was calculated as the average prediction error across the four standardized outcomes [43]:

$$L = \frac{1}{4N} \sum_{i=1}^{N} \sum_{k=1}^{4} (y_{ik}^{*} - \hat{y}_{ik}^{*})^2 \tag{4}$$

where N is the number of cases, y_{ik}^{*} and $\hat{y}_{ik}^{*}$ denote the standardized actual and predicted values of outcome k for case i, respectively, and the four outcomes correspond to *FIRR*, *FNPV*, *Pt*, and *DSCR*. Within the unified model, the raw importance of predictor j, denoted by I_j, was determined by its cumulative contribution to reducing the joint loss across all tree splits. The final weight was obtained by normalizing the raw importance scores [43]:

$$w_j = \frac{I_j}{\sum_{j=1}^{p} I_j}, \qquad \sum_{j=1}^{p} w_j = 1 \tag{5}$$

where p is the total number of predictors and ω_j is the normalized predictive-importance weight of predictor j. The feature-importance scores were normalized to obtain the predictive-importance weights reported in Table 2. Each predictive-importance

weight represents a predictor's relative contribution to reducing the joint prediction loss across the four standardized financial outcomes. Financing inputs, regional fiscal conditions, and resource development modes generally received higher weights, suggesting greater predictive importance within the current dataset and model settings. These weights were subsequently used in the weighted similarity calculation to prioritize project characteristics relevant to financial performance.

Table 2. Indicator weights for the GBDT model.

Indicator	Weight	Ranking
Capital	0.40332801	1
Regional development	0.09732181	2
Loan funds	0.09676178	3
Solid waste treatment	0.09672134	4
Government debt ratio	0.05793913	5
Ecological protection and restoration	0.04801013	6
Government debt	0.04340226	7
Ecological health and wellness	0.02701664	8
Industrial feedback	0.02496786	9
Total investment	0.02483687	10
Loan term	0.02380709	11
Regional GDP	0.01205093	12
Fiscal revenue	0.01108811	13
Comprehensive governance of key sea areas	0.01079198	14
Ecological agriculture	0.01079158	15
Soil pollution prevention and control	0.00742710	16
Cultural tourism	0.00168052	17
Resource utilization	0.00162557	18
Water ecological environment protection	0.00041594	19
Ecological industry	0.00001242	20
Agricultural and rural pollution control	0.00000293	21
Air pollution prevention and control	0.00000000	22
Other environmental governance	0.00000000	23

3.3. Case Retrieval

Case retrieval is the key step for reusing historical experience. In this study, the target project was compared with 126 historical EOD cases in the case database. Project ID, project name, implementing entity, and location were used only for case identification and presentation and were excluded from the similarity calculation. Regional differences were instead represented by GDP, fiscal revenue, and government debt ratio. Therefore, global similarity was calculated using only the 23 GBDT-weighted indicators listed in Table 2. For numerical indicators, local similarity was calculated as [44]:

$$s_j(T, C_i) = \max\left(0, 1 - \frac{\left|x_{Tj} - x_{ij}\right|}{x_j^{\max} - x_j^{\min}}\right) \tag{6}$$

For Boolean indicators, the similarity was set to 1 when the two values were identical and 0 otherwise. The global similarity was then calculated as [44]:

$$S(T, C_i) = \sum_{j=1}^{23} w_j s_j(T, C_i), \qquad \sum_{j=1}^{23} w_j = 1 \tag{7}$$

where w_j is the GBDT-derived predictive-importance weight reported in Table 2. Considering that historical cases may not fully match a target project, this study introduced a

case review and scenario-adjustment mechanism to support experience reuse. The distinction between case retrieval and subsequent reuse or adaptation follows the established CBR process [45,46]. For each target project, all historical cases are ranked by their calculated global similarity, and the three highest-ranked cases are retrieved as the initial candidate set. Retrieving three similar cases has precedent in financial CBR applications, although this does not establish three as the optimal retrieval size for EOD projects. Similarity thresholds have also been investigated in construction-related CBR applications. For example, García de Soto and Adey [47] reported that a 90% threshold yielded the best results in their construction resource estimation study. Drawing on the authors' practical experience in collecting, screening, organizing, and evaluating EOD project cases, this study adopted 60% and 85% as preliminary operational thresholds to guide the subsequent treatment of each retrieved candidate. These thresholds are applied after similarity calculation and ranking, and therefore do not affect the similarity scores, case rankings, or selection of the initial three candidates [48]. Candidates with similarity below 60% do not proceed to subsequent case retrieval or scenario adjustment [49]. Candidates with similarity between 60% and 85%, inclusive, undergo scenario-based adaptation of planning variables that have not yet been finalized, such as resource balancing portfolios or financing arrangements, followed by professional review. Candidates with similarity above 85% proceed to experience reuse following professional verification [32,47]. Thus, the framework consistently retrieves the three highest-ranked cases, while only candidates meeting the minimum similarity threshold of 60% are eligible to proceed through the corresponding review and reuse pathway. If all three candidates have similarity below 60%, subsequent case retrieval is suspended until additional information or more suitable historical cases become available.

At the case retrieval stage, the three highest-ranked historical cases were selected as the primary sources of decision evidence. Structured information on industrial portfolio configurations, financing arrangements, policy instruments, implementation sequences, and risk-control measures was extracted from these cases and their supporting documents. Numerical recommendations, such as financing proportions and loan terms, were formulated by comparing the corresponding values across the retrieved cases, whereas categorical recommendations were derived from practices commonly adopted across multiple cases.

3.4. Financial Indicator Prediction

The GBDT model progressively fits residuals through multiple regression trees and continuously corrects prediction errors, thereby achieving a high-precision approximation of complex nonlinear relationships between EOD project features and financial performance. In this study, the prediction module takes the standardized case representation as the input and estimates the key financial indicators of the target project, including *FIRR*, *FNPV*, *Pt*, and *DSCR*. The input feature vector of each case can be expressed as:

$$X_i = \{x_{i1}, x_{i2}, ..., x_{in}\} \tag{8}$$

where X_i denotes the standardized feature vector of case *i*, and x_{ij} represents the value of the *jth* input indicator. These indicators include investment scale, financing structure, regional fiscal conditions, environmental problem types, and resource balancing modes. The corresponding output vector is expressed as:

$$Y_i = \{FIRR_i, FNPV_i, Pt_i, DSCR_i\} \tag{9}$$

where Y_i denotes the financial performance indicators of case *i*.

Based on the 32 historical EOD projects that contain both X_i and Y_i, the GBDT model learns the mapping relationship between input features and output indicators:

$$\hat{Y} = F(X) = \sum_{m=1}^{M} f_m(X) \tag{10}$$

where M is the number of regression trees, $f_m(X)$ denotes the prediction result of the m-th tree, and $\hat{Y}$ represents the predicted financial outcome vector comprising *FIRR*, *FNPV*, *Pt*, and *DSCR*. During model training, the first regression tree provides an initial estimate, and each subsequent tree fits the residual between the actual value and the current predicted value. The iterative updating process can be expressed as:

$$\hat{Y}^m = \hat{Y}^{m-1} + \eta f_m(X) \tag{11}$$

where $\hat{Y}^m$ is the prediction result after the m-th iteration, η is the learning rate, and $f_m(X)$ is the newly generated regression tree used to correct the previous prediction error. Through this residual fitting mechanism, the model gradually reduces the prediction deviation and improves its ability to capture nonlinear relationships among project features, financing conditions, and financial outcomes.

Figure 4 illustrates the case prediction process constructed in this paper. First, the historical EOD cases are transformed into structured feature vectors according to the case triple representation. Second, the 23 input features are entered into the GBDT model, and the financial indicators of historical cases are used as supervised learning targets. Third, the model continuously constructs regression trees through residual fitting and error correction until the prediction performance reaches a stable state. Finally, the standardized feature vector of the target project is input into the trained model to obtain the predicted values of *FIRR*, *FNPV*, *Pt*, and *DSCR*. The prediction results are then linked with case retrieval so that historical experience and quantitative analysis jointly support project feasibility assessment and scheme comparison.

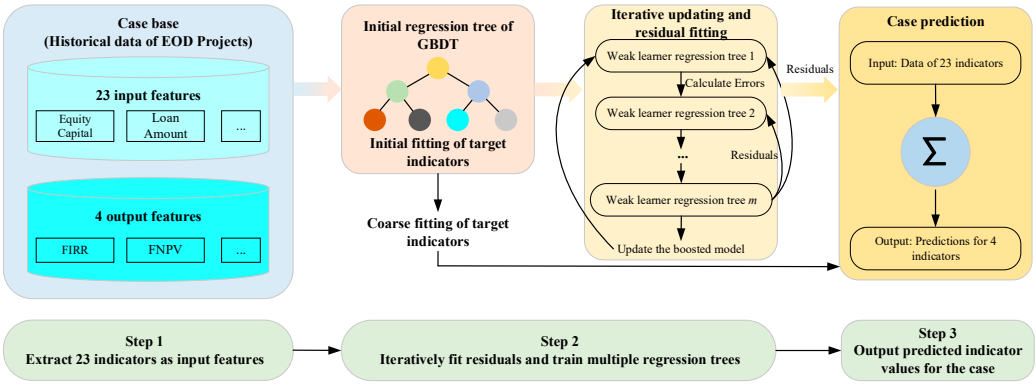


Figure 4. The case prediction process.

During prediction, the indicator weights are not manually assigned to the model, but are implicitly reflected through the node-splitting and feature contribution mechanisms of GBDT. Indicators with stronger explanatory power, such as equity capital, loan amount, district development, and government debt ratio, are more likely to be selected as splitting variables in regression trees and therefore play a more important role in final prediction. Indicators with lower feature importance provide supplementary corrections within local intervals. In this way, the model learns the nonlinear relationships between

project features and financial performance from historical cases and transfers these patterns to new projects. Combined with similar case retrieval and scheme generation, the prediction results provide quantitative support for assessing profitability, payback characteristics, and debt-servicing capacity, thereby forming a closed decision-support loop for EOD project appraisal and optimization.

4. Case Study

4.1. Case Selection and Background

The Xibei Canal EOD project was selected to illustrate the application of the proposed method for three reasons. First, it was included in the first batch of EOD pilot projects in Jiangsu Province, China, in April 2023 and subsequently incorporated into the national database of ecological and environmental projects receiving public financial support in December 2023. Second, the project has completed financing close and entered the construction stage, providing a practical context for demonstrating planning-stage financial assessment and resource balancing. Third, its bank credit approval report provides documented financial appraisal estimates and implementation plans, supporting case representation, comparable-case retrieval, and comparison with model predictions.

The Xibei Canal EOD project is located in Wuxi, Jiangsu Province, and focuses on water ecological restoration, river regulation, dredging, revetment improvement, sewage outlet remediation, and riparian ecological restoration along the Xibei Canal. To support ecological governance investment, the project introduces a green and low-carbon industrial park as the primary resource balancing mechanism, utilizing industrial development and operational revenues to offset environmental governance costs. Therefore, this case exemplifies the examination of both financial feasibility and resource balancing under the EOD model.

According to the case triple structure $C = (ID, P, S)$ constructed in this study, the project can be represented across three dimensions. In terms of case identification *ID*, the project is named the Xibei Canal EOD Project, the implementing entity is Wuxi Jishi Investment Development Co., Ltd., and the project is located in Wuxi, Jiangsu Province. Its total investment is USD 706.94 million, its equity capital is USD 143.51 million, its loan amount is USD 563.42 million, and its loan term is 23 years. In addition, regional fiscal indicators such as gross domestic product, fiscal revenue, government debt, and government debt ratio are also incorporated. In terms of problem description *P*, the core environmental issues addressed by the project include river regulation, dredging, revetment improvement, remediation of sewage outlets along the river, and riparian ecological restoration, all of which can be categorized as water ecological environment protection. In terms of solution *S*, the project introduces the construction of a green and low-carbon industrial park on the basis of ecological and environmental restoration, and uses the returns generated by industrial upgrading to feed back into ecological governance investment. Table 3 presents the standardized case representation results of the Xibei Canal EOD Project. It can be seen that the case has complete data and satisfies the input requirements of similar case retrieval and financial indicator prediction. The project is highly typical in terms of financing structure, regional fiscal conditions, environmental problem type, and resource balancing mode, thereby providing a sound sample for testing the applicability of the proposed method under complex EOD project scenarios.

https://doi.org/10.3390/su182111380

Table 3. Xibei Canal EOD project.

Triple Dimension	Core Field	Field Value
Case identification (ID)	Project ID	00127
	Project name	Xibei Canal (Wuxi Xishan Section) EOD project
	Implementing entity	Wuxi Jishi Investment and Development Co., Ltd.
	Location	Wuxi City, Jiangsu Province
	Total investment	USD 706.94 million
	Paid-in capital	USD 143.51 million
	Loan funds	USD 563.42 million
	Loan term	23 years
	Regional GDP	USD 239.87 billion
	Fiscal revenue	USD 29.98 billion
	Government debt	USD 38.49 billion
	Government debt ratio	128.41%
Problem description (P)	Environmental issues	Water ecological environment protection
Solution (S)	Resource balancing	Eco-industry

This case embodies the dual attributes of a typical watershed ecological governance project and an industry feedback-based EOD project. It involves a large-scale public welfare-oriented ecological governance investment and therefore has a clear environmental governance orientation. By introducing the construction of a green and low-carbon industrial park to establish a revenue compensation pathway, it also reflects the typical implementation logic of EOD projects, namely, ecological governance plus industrial introduction. For this reason, the case is not only suitable for examining the performance of the integrated model in environmental problem identification, similar case matching, and financing structure reference, but is also appropriate for evaluating the effectiveness of the model in predicting financial and risk indicators.

4.2. Similar Case Retrieval Results

After standardizing the target case, similarity retrieval was conducted against the 126 historical EOD cases through local similarity calculation and weighted global aggregation. Figure 5 presents the target-project input interface, which records regional economic conditions, basic project information, financing arrangements, environmental issues, and resource-balancing options. For the Xibei Canal project, aquatic ecosystem protection was selected as the environmental issue, while ecological industry and industrial cross-subsidization were specified as the resource-balancing options. The interface was configured to return the three highest-ranked cases, with a similarity threshold of 85% for subsequent experience-reuse assessment. Project identification fields were retained for presentation, while the 23 indicators listed in Table 2 were used to calculate local similarities and aggregate them using GBDT-derived predictive-importance weights. The resulting global similarities of the three highest-ranked cases were 91.02%, 90.26%, and 89.52%, respectively. All three exceeded the baseline upper threshold and were therefore eligible for experience reuse following professional verification.

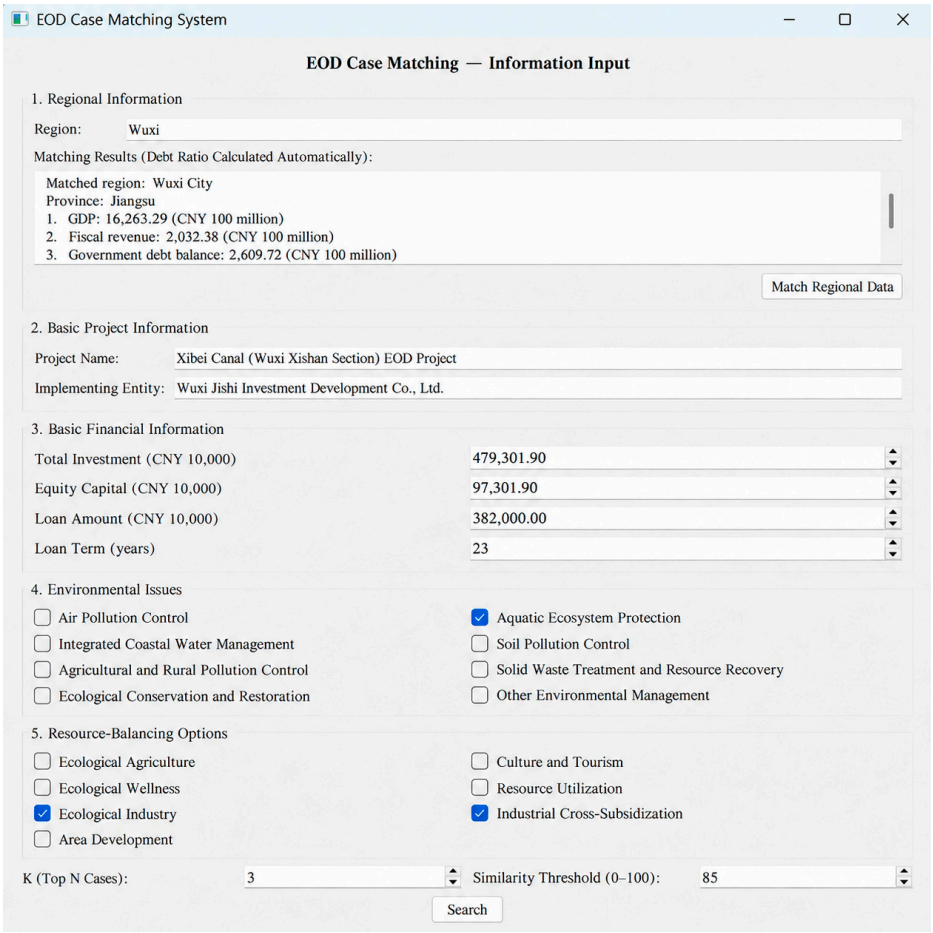
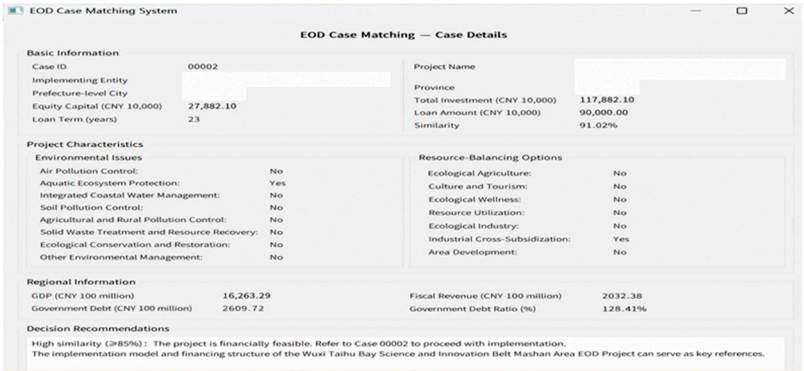


Figure 5. System case information input interface.

Figure 6 presents the three highest-ranked historical cases and identifies how their experience can inform the target project. Cases 00002, 00007, and 00020 achieved similarities of 91.02%, 90.26%, and 89.52%, respectively. All three were about aquatic ecosystem protection and adopted industrial cross-subsidization, providing relevant references for linking ecological governance with industrial revenue generation. Case 00002 was in Wuxi, the same city as the target project, and provided the closest financing reference. Its equity and loan proportions were approximately 23.65% and 76.35%, respectively, compared with 20.30% and 79.70% for the target project, while both have a 23-year loan term. Accordingly, Case 00002's financing structure and loan maturity served as references for reviewing the target project's proposed financing arrangement, with repayment arrangements adapted to the target project's cash-flow profile.


EOD Case Matching System

EOD Case Matching — Case Details

Basic Information

Case ID	00002	Project Name	
Implementing Entity		Province	
Prefecture-level City		Total Investment (CNY 10,000)	117,882.10
Equity Capital (CNY 10,000)	27,882.10	Loan Amount (CNY 10,000)	90,000.00
Loan Term (years)	23	Similarity	91.02%

Project Characteristics

Environmental Issues

Air Pollution Control:	No
Aquatic Ecosystem Protection:	Yes
Integrated Coastal Water Management:	No
Soil Pollution Control:	No
Agricultural and Rural Pollution Control:	No
Solid Waste Treatment and Resource Recovery:	No
Ecological Conservation and Restoration:	No
Other Environmental Management:	No

Resource-Balancing Options

Ecological Agriculture:	No
Culture and Tourism:	No
Ecological Wellness:	No
Resource Utilization:	No
Ecological Industry:	No
Industrial Cross-Subsidization:	Yes
Area Development:	No

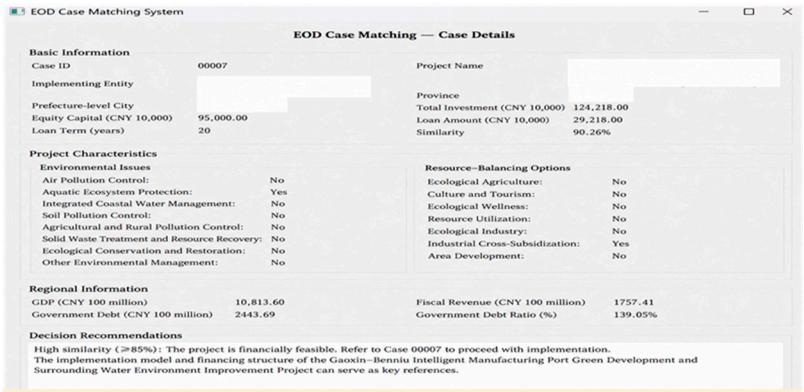
Regional Information

GDP (CNY 100 million)	16,263.29	Fiscal Revenue (CNY 100 million)	2032.38
Government Debt (CNY 100 million)	2609.72	Government Debt Ratio (%)	128.41%

Decision Recommendations

High similarity (≥85%): The project is financially feasible. Refer to Case 00002 to proceed with implementation.
The implementation model and financing structure of the Wuxi Taihu Bay Science and Innovation Belt Mashan Area EOD Project can serve as key references.

Use the 23-year loan term and equity–loan structure (23.65% equity and 76.35% loans) as references for reviewing the target pro-ject's proposed financing arrangement of 20.30% equity and 79.70% loans. Adapt repayment arrangements to the target pro-ject's cash-flow profile.


EOD Case Matching System

EOD Case Matching — Case Details

Basic Information

Case ID	00007	Project Name	
Implementing Entity		Province	
Prefecture-level City		Total Investment (CNY 10,000)	124,218.00
Equity Capital (CNY 10,000)	95,000.00	Loan Amount (CNY 10,000)	29,218.00
Loan Term (years)	20	Similarity	90.26%

Project Characteristics

Environmental Issues

Air Pollution Control:	No
Aquatic Ecosystem Protection:	Yes
Integrated Coastal Water Management:	No
Soil Pollution Control:	No
Agricultural and Rural Pollution Control:	No
Solid Waste Treatment and Resource Recovery:	No
Ecological Conservation and Restoration:	No
Other Environmental Management:	No

Resource-Balancing Options

Ecological Agriculture:	No
Culture and Tourism:	No
Ecological Wellness:	No
Resource Utilization:	No
Ecological Industry:	No
Industrial Cross-Subsidization:	Yes
Area Development:	No

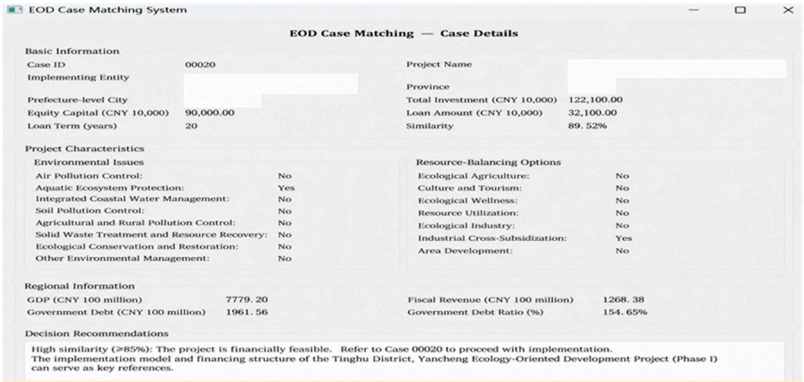
Regional Information

GDP (CNY 100 million)	10,813.60	Fiscal Revenue (CNY 100 million)	1757.41
Government Debt (CNY 100 million)	2443.69	Government Debt Ratio (%)	139.05%

Decision Recommendations

High similarity (≥85%): The project is financially feasible. Refer to Case 00007 to proceed with implementation.
The implementation model and financing structure of the Gaoxin–Benniu Intelligent Manufacturing Port Green Development and Surrounding Water Environment Improvement Project can serve as key references.

Transfer the industrial cross-subsidization approach to support the target project's resource-balancing scheme. Use its equity-intensive financing structure (76.48% equity) as an alternative scenario for assessing whether additional equity participation could reduce borrowing requirements.


EOD Case Matching System

EOD Case Matching — Case Details

Basic Information

Case ID	00020	Project Name	
Implementing Entity		Province	
Prefecture-level City		Total Investment (CNY 10,000)	122,100.00
Equity Capital (CNY 10,000)	90,000.00	Loan Amount (CNY 10,000)	32,100.00
Loan Term (years)	20	Similarity	89.52%

Project Characteristics

Environmental Issues

Air Pollution Control:	No
Aquatic Ecosystem Protection:	Yes
Integrated Coastal Water Management:	No
Soil Pollution Control:	No
Agricultural and Rural Pollution Control:	No
Solid Waste Treatment and Resource Recovery:	No
Ecological Conservation and Restoration:	No
Other Environmental Management:	No

Resource-Balancing Options

Ecological Agriculture:	No
Culture and Tourism:	No
Ecological Wellness:	No
Resource Utilization:	No
Ecological Industry:	No
Industrial Cross-Subsidization:	Yes
Area Development:	No

Regional Information

GDP (CNY 100 million)	7779.20	Fiscal Revenue (CNY 100 million)	1268.38
Government Debt (CNY 100 million)	1961.56	Government Debt Ratio (%)	154.65%

Decision Recommendations

High similarity (≥85%): The project is financially feasible. Refer to Case 00020 to proceed with implementation.
The implementation model and financing structure of the Tinghu District, Yancheng Ecology-Oriented Development Project (Phase I) can serve as key references.

Apply the experience of linking water-environment governance with industrial revenue generation to review the target project's revenue-compensation pathway. Use its financing structure (73.71% equity) and 20-year loan term as references for comparing alternative financing scenarios.

Figure 6. Retrieved similar cases and their implications for experience transfer and adaptation (Specific place names and other sensitive information in the figure have been masked to protect commercial confidentiality).

Cases 00007 and 00020 provided complementary references despite their substantially different financing proportions from the target project. Case 00007 had an equity proportion of approximately 76.48%, supporting the consideration of an alternative financing scenario in which additional equity participation reduces borrowing requirements. Its industrial cross-subsidization approach also informed the target project's re-

source-balancing scheme. Case 00020 combined aquatic ecosystem protection with industrial cross-subsidization, providing a reference for reviewing the target project's revenue-compensation pathway. Its equity proportion of approximately 73.71% and 20-year loan term informed the comparison of alternative financing scenarios. Thus, recommendations on the target project's finance arrangement were primarily compared with Case 00002, while its complementary resource-balancing experience and equity-intensive financing alternatives were drawn from Cases 00007 and 00020. Although all three cases exceeded the 85% threshold and were eligible for experience reuse following professional verification, their financing differences required project-specific adaptation, particularly given the target project's greater reliance on borrowing.

4.3. Prediction Results

The target-project inputs comprise regional economic and government debt conditions, proposed financing arrangements, environmental remediation needs, and resource-balancing options. The CBR component retrieves the three most similar historical cases and assesses their eligibility for subsequent processing. Cases below 60% are excluded from experience reuse, whereas those between 60% and 85%, inclusive, require scenario-based adaptation and reassessment of planning variables that have not been finalized. Cases above 85% are eligible for experience reuse following professional verification. As shown in Figure 7, Cases 00002, 00007, and 00020 achieve similarities of 91.02%, 90.26%, and 89.52%, respectively, and therefore provide historical references for the target project. The GBDT component predicts financial indicators from the target-project inputs, providing quantitative evidence to complement the retrieved experience.

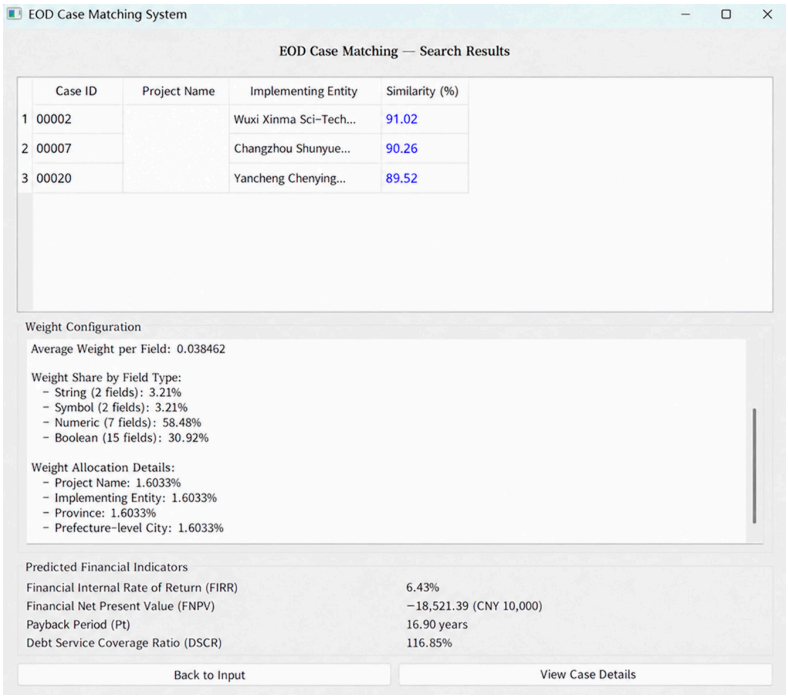


Figure 7. Financial and risk indicator prediction (specific place names and other sensitive information in the figure have been masked to protect commercial confidentiality).

Figure 7 reports a predicted FIRR of 6.43%, an FNPV of −18,521.39 in units of CNY 10,000, a Pt of 16.90 years, and a DSCR of 116.85%. These indicators characterize the project's profitability, investment recovery, and debt-servicing capacity. The predicted payback period indicates a long investment-recovery horizon, while the DSCR suggests that cash available for debt service exceeds the corresponding repayment obligations under

the evaluated conditions. Together with the predicted FIRR and FNPV, these results provide a basis for comparing financing and resource-balancing scenarios and identifying aspects requiring further project-specific assessment.

The predictions are interpreted alongside the case-specific experience presented in Figure 6 to develop financing and resource-balancing recommendations. Case 00002 provides a reference for the target project's equity–loan combination and 23-year loan term, with repayment arrangements reviewed against its cash-flow profile. The higher equity proportions of Cases 00007 and 00020 inform alternative scenarios involving additional equity participation and reduced borrowing requirements. Their industrial cross-subsidization experience also supports reviewing how revenues from the proposed green and low-carbon industrial park can compensate for ecological governance expenditure. The combined output therefore links comparable historical cases, predicted financial indicators, and financing alternatives to support scheme comparison and refinement.

4.4. Comparison with Project Financial Appraisal Estimates

Table 4 compares the GBDT predictions with the target project's financial appraisal estimates for *FIRR*, *FNPV*, *Pt*, and *DSCR*. The predicted *Pt* is 16.9 years, compared with the appraisal estimate of 15.9 years, yielding a relative absolute deviation of 6.29%. The predicted *DSCR* is 116.85%, compared with 132.8%, with a deviation of 12.01%. Larger deviations occur for *FIRR* and *FNPV*. The predicted *FIRR* is 6.43%, compared with 4.87%, corresponding to a difference of 1.56 percentage points and a relative absolute deviation of 32.03%. The predicted *FNPV* is USD −27.56 million, compared with USD -37.75 million, yielding a deviation of 26.99%. Given the sensitivity of FNPV to changes in cash flows [50], this prediction deviation may be considered acceptable for the preliminary financial screening purpose of this study. Overall, the predictions are closer to the appraisal estimates for investment recovery and debt servicing than for profitability and net present value.

Table 4. Comparison of model predictions with financial appraisal estimates for the Xibei Canal project.

Indicator	Financial Appraisal Estimate	Predicted Value	Relative Absolute Deviation (%)
FIRR	4.87%	6.43%	32.03%
FNPV	USD −37.75 million	USD −27.56 million	26.99%
Pt	15.9 years	16.9 years	6.29%
DSCR	132.8%	116.85%	12.01%

The differences across indicators provide a basis for interpreting the predictions in preliminary project appraisal. The relatively large percentage deviation in *FIRR* partly reflects its small appraisal value, while its sensitivity to cash-flow timing and magnitude may also contribute to prediction differences [51]. The *FNPV* deviation indicates that the projected revenue–cost balance requires further project-specific examination. Previous studies [28,52] have demonstrated the usefulness of data-driven and case-based methods for early-stage estimation and decision support despite variation in prediction errors across outcomes. In this application, the predicted indicators are therefore considered alongside the financial appraisal estimates and retrieved case experience. Case 00002 provides a comparable financing reference, while Cases 00007 and 00020 inform alternatives involving greater equity participation. This linkage makes the predictions interpretable in relation to specific financing choices and supports subsequent scheme comparison and professional review.

5. Discussion

5.1. Sensitivity and Scenario-Based Response-Surface Analyses

Building on the preceding prediction analysis, the GBDT model is used to predict the four financial indicators under different total investment and regional GDP scenarios. Figure 8 shows how these indicators vary with total investment under fixed regional conditions, while Figure 9 presents their responses to joint variations in total investment and regional GDP.

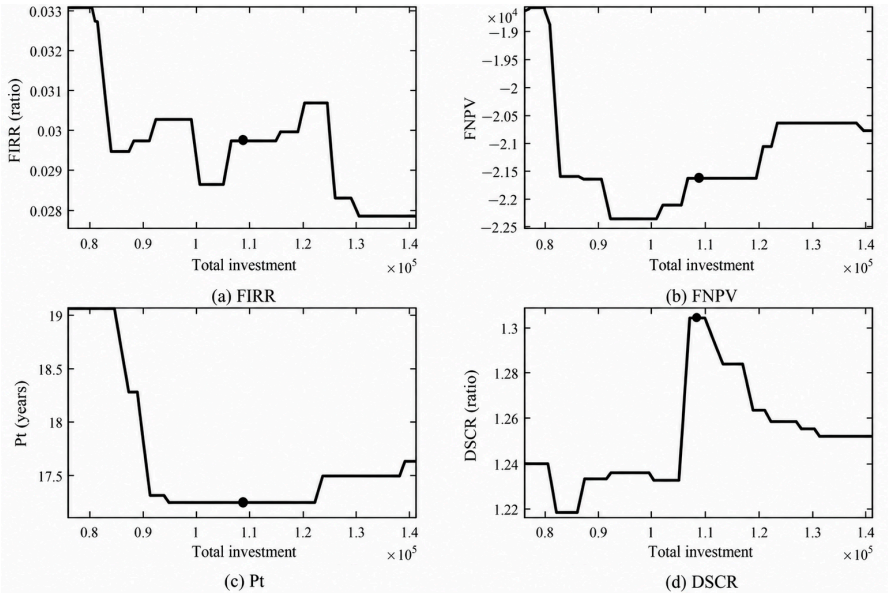


Figure 8. Sensitivity analysis of total investment.

Figure 8 presents the response curves of the four financial indicators over a total investment range of 0.75×10^5 to 1.40×10^5. *FIRR* fluctuates at intermediate investment levels and declines markedly when investment exceeds approximately 1.25×10^5. *Pt* decreases sharply at lower investment levels, remains at approximately 17.3 years across a broad intermediate interval, and increases slightly beyond approximately 1.23×10^5. *DSCR* rises substantially around 1.07×10^5, forms a short plateau, and then gradually declines before stabilizing at higher investment levels. The indicators differ in their response magnitudes and turning points, providing a basis for distinguishing investment intervals and comparing alternative schemes.

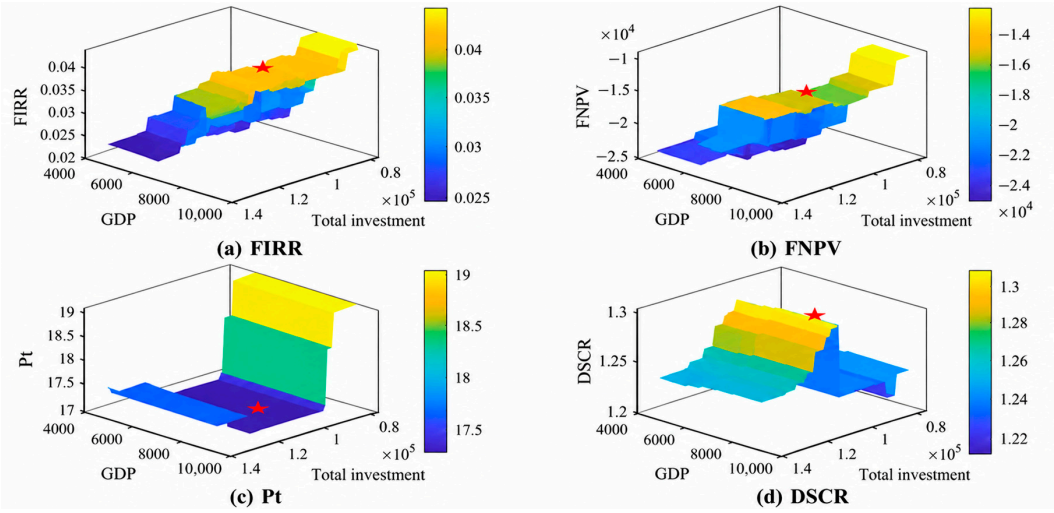


Figure 9. Response surfaces of financial indicators under different total-investment and regional-GDP scenarios.

Figure 9 presents the financial indicator responses to joint variations in total investment and regional GDP. The red stars mark selected reference scenarios on the respective surfaces. *FIRR* and *FNPV* generally increase with regional GDP and exhibit stepped plateaus across different investment intervals. *Pt* shows a pronounced transition between investment intervals and remains relatively stable across a broad region after reaching the lower plateau. *DSCR* exhibits a ridge-shaped distribution, with higher values concentrated within an intermediate investment interval, followed by a gradual decline. Compared with Figure 8, Figure 9 further depicts response differences under varying regional economic conditions, facilitating the comparison of alternative investment scenarios.

Together, the two figures help identify investment intervals associated with pronounced changes in financial indicators and compare scenario performance under different regional economic conditions. In project appraisal, since regional GDP cannot be manipulated by the project, these comparisons help screen proper investment scales, and can be combined with financing arrangements and resource-balancing strategies drawn from similar cases to inform subsequent scheme refinement.

5.2. Sensitivity Analysis of Similarity Thresholds

To examine the effects of similarity thresholds on historical case screening, alternative thresholds were applied to the ranked cases while keeping the target-project inputs and similarity weights unchanged. Following the similarity screening approach adopted by Asim et al. [53], 60% was set as the lower threshold for cases to enter subsequent analysis. Cases below this threshold are excluded from experience reuse, and additional project information or scheme revision is recommended before reassessment.

The upper threshold of 85% was examined, as the lowest similarity score for the Xibei Canal project was 89.52%. We therefore set the upper threshold to be 86%, 87%, 88%, 89%, 90% and 91%, respectively, and the results are shown in Figure 10. At a screening threshold of 86%, ten candidate cases remain eligible, providing a sufficient pool for selecting the top three. Accordingly, this study adopts 85% as the operational threshold for experience reuse, maintaining a high similarity requirement while retaining some flexibility for case comparison and professional verification. Figure 10 shows that progressively stricter thresholds reduce the candidate set, while the similarity scores and relative ordering of the retained cases remain unchanged. Increasing the threshold to 90% leaves only two eligible cases, whereas a threshold of 91% retains only Case 00002. Neither setting satisfies the requirement to recommend three cases. The 85% threshold therefore maintains a high similarity requirement while providing sufficient candidates for case recommendation.

	Case ID	Project Name	Implementing Entity	Similarity (%)
1	00002	Wuxi Taihu Bay...	Wuxi Xinma Sci-Tech...	91.02
2	00007	Gaoxin–Benniu...	Changzhou Shunyue...	90.26
3	00020	Yancheng Tinghu...	Yancheng Chenying...	89.52
4	00037	Weitang, Xiangcheng...	Suzhou Zhenweitang...	88.47
5	00001	Taixing High-Tech...	Taixing Zhiguang...	88.27
6	00017	Shaoyang National...	Shaoyang Baoqing...	87.08
7	00060	Hunan Chenglingji...	Hunan Lingang...	87.01
8	00072	Wuan Yudai River...	Wuan Urban Construction...	86.94
9	00048	Suichang Xianxia Lake...	Suichang County Government	86.89
10	00014	Quzhou Kecheng...	Quzhou Sichi Reservoir...	86.83

(a) 86% threshold

	Case ID	Project Name	Implementing Entity	Similarity (%)
1	00002	Wuxi Taihu Bay...	Wuxi Xinma Sci-Tech...	91.02
2	00007	Gaoxin–Benniu...	Changzhou Shunyue...	90.26
3	00020	Yancheng Tinghu...	Yancheng Chenying...	89.52
4	00037	Weitang, Xiangcheng...	Suzhou Zhenweitang...	88.47
5	00001	Taixing High-Tech...	Taixing Zhiguang...	88.27
6	00017	Shaoyang National...	Shaoyang Baoqing...	87.08
7	00060	Hunan Chenglingji...	Hunan Lingang...	87.01

(b) 87% threshold

	Case ID	Project Name	Implementing Entity	Similarity (%)
1	00002	Wuxi Taihu Bay...	Wuxi Xinma Sci-Tech...	91.02
2	00007	Gaoxin–Benniu...	Changzhou Shunyue...	90.26
3	00020	Yancheng Tinghu...	Yancheng Chenying...	89.52
4	00037	Weitang, Xiangcheng...	Suzhou Zhenweitang...	88.47
5	00001	Taixing High-Tech...	Taixing Zhiguang...	88.27

(c) 88% threshold

	Case ID	Project Name	Implementing Entity	Similarity (%)
1	00002	Wuxi Taihu Bay...	Wuxi Xinma Sci-Tech...	91.02
2	00007	Gaoxin–Benniu...	Changzhou Shunyue...	90.26
3	00020	Yancheng Tinghu...	Yancheng Chenying...	89.52

(d) 89% threshold

	Case ID	Project Name	Implementing Entity	Similarity (%)
1	00002	Wuxi Taihu Bay...	Wuxi Xinma Sci-Tech...	91.02
2	00007	Gaoxin–Benniu...	Changzhou Shunyue...	90.26

(e) 90% threshold

	Case ID	Project Name	Implementing Entity	Similarity (%)
1	00002	Wuxi Taihu Bay...	Wuxi Xinma Sci-Tech...	91.02

(f) 91% threshold

https://doi.org/10.3390/su182111380

Figure 10. Case screening results under different similarity thresholds.

5.3. Implications for Theory and Practice

From the perspective of methodological composition, the EOD project decision-making method proposed in this study, which integrates CBR and ML, is essentially an organic combination of two decision-making logics, namely, experience reuse and data-driven analysis. For EOD projects, relying solely on human experience for project planning and appraisal may allow decision makers to draw, to a certain extent, on prior practice, but it often suffers from insufficient knowledge accumulation, unstable experience transfer, and difficulty in quantifying the decision-making process [54,55]. By contrast, relying solely on ML models for financial prediction may improve the quantitative capability of indicator analysis, but it usually cannot provide interpretable case references or transferable scheme support [56]. The advantage of the proposed method lies in integrating CBR-based historical case matching and experience reuse with ML-based indicator weight identification and financial prediction. Through standardized case representation, GBDT-derived objective weighting, and the linkage of case retrieval, revision, reuse, and prediction, the method transforms EOD project decision-making from experience-based static judgment into a structured, repeatable, and quantitative decision support process. Compared with traditional expert judgment or single prediction models, it improves transparency and reusability while retaining both experience transfer and scheme reference capabilities, making it more suitable for complex EOD project contexts.

In practice, this method is particularly suitable for project types characterized by strong contextual dependence and multifactor coupling. Specifically, one category includes projects in which significant differences exist among environmental problem types, resource introduction modes, and regional conditions, making it difficult to directly apply a unified empirical rule [4]. Another category includes projects that require both reference to mature existing cases and quantitative judgment of key financial and risk indicators [57]. A further category includes complex projects whose schemes are not determined by a single profitability indicator, but are jointly influenced by environmental governance investment, industrial feedback capacity, financing structure, and regional fiscal conditions [58]. EOD projects happen to possess all of the above characteristics simultaneously, and the proposed method therefore shows strong adaptability in this field. As demonstrated by the empirical results presented above, the method can not only identify highly similar reference cases, but can also generate operational reference schemes in combination with the context of the target project. This indicates that it is not merely a prediction tool, but rather a comprehensive decision support method oriented toward project development, screening, and appraisal.

6. Conclusions

This study developed a hybrid CBR-ML decision-support method for the preliminary evaluation of financial feasibility and resource balancing in EOD projects. Specifically, a standardized case representation structure comprising case identification, problem description, and solution was established, enabling heterogeneous information from EOD projects to be organized into reusable and computable case knowledge. The proposed framework integrates GBDT-based predictive-importance identification and financial prediction with CBR-based case retrieval, revision, and reuse, thereby linking historical experience with quantitative analysis, and was illustrated through its application to the Xibei Canal EOD project. Findings showed that the three highest-ranked cases achieved global similarities of 91.02%, 90.26%, and 89.52%, respectively. Their similarities were reflected in environmental governance requirements, resource balancing modes, financing arrangements, and regional conditions, demonstrating the ability of the method

to identify practically comparable cases. Additionally, equity capital, loan amount, district development, and government debt ratio showed relatively high predictive importance for the four financial outcomes under the current dataset and model settings.

Based on these findings, several practical recommendations are proposed. First, relevant authorities should establish standardized EOD project information-sharing and evaluation mechanisms to reduce institutional barriers and support the continuous accumulation and reuse of project experience. Second, project developers and financial institutions should coordinate equity capital, long-term loans, repayment arrangements, and revenue-generating resources according to project cash-flow characteristics, rather than relying excessively on a single financing source or profitability indicator. Third, ecological-environmental, development and reform, financial, planning, and sectoral authorities should strengthen cross-sector coordination in project screening, resource allocation, financing review, and implementation supervision. The proposed method can support these activities through comparable-case retrieval, preliminary financial prediction, and resource balancing scheme comparison, while final investment decisions should still incorporate detailed project-specific analyses and professional judgment. Although some prediction deviations remain, the framework's accuracy is partly constrained by the quality and coverage of the available case data. As more high-quality and representative project data become available and are incorporated into model training, prediction accuracy is expected to improve. Future research can therefore focus on expanding the case base, improving data quality, and examining alternative similarity thresholds to assess their effects on case retrieval eligibility and subsequent recommendations, supporting the continuous refinement of the framework.

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Abbreviations

The following abbreviations are used in this manuscript:

EOD	Ecology-oriented development
PPP	Public–private partnership
FIRR	Financial internal rate of return
FNPV	Financial net present value

Pt	Payback time
DSCR	Debt service coverage ratio
CBR	Case-based reasoning
GBDT	Gradient boosting decision tree
SVM	Support vector machine
RF	Random forest
LR	Linear regression

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