

Designing an Explainable AI-Based Decision Support Model for Evaluating Open Innovation in the Food Supply Chain

Sajjad Momeni¹ , Hossein Amoozad Khalili² , Ehsan Momenic³ , Zahra Saeidi Mobarakeh⁴ 

1. Ph.D. Candidate, Department of Management, Ro.C., Islamic Azad University, Roudehen, Iran. Email: Sajjad.momeni@iau.ir
2. Corresponding author, Associate Professor, Department of Industrial Engineering, Sar.C., Islamic Azad University, Sari, Iran. Email: ho.amoozad@iau.ac.ir
3. Assistant Professor, Department of Industrial Engineering, Par.C., Islamic Azad University, Pardis, Iran. Email: ehs_momeni@iau.ac.ir
4. Assistant Professor, Department of Industrial Engineering, CT.C., Islamic Azad University, Tehran, Iran. Email: z.saeidimobarakeh@iau.ac.ir

Article Info	ABSTRACT
Article type: Research Article Article history: Received 17 May 2026 Received in revised form 20 June 2026 Accepted 17 September 2026 Published online 1 October 2026 Keywords: open innovation, supply chain, food industry, explainable artificial intelligence, data-driven model	Open innovation plays a significant role in enhancing the competitiveness and sustainability of supply chains, particularly within the food industry. However, evaluating the level of open innovation remains a challenging issue due to its multidimensional and complex nature. This study aims to develop a data-driven and explainable framework for assessing the level of open innovation in the food supply chain. First, the evaluation indicators of open innovation were identified and finalized through a comprehensive literature review and expert opinions. Subsequently, the relative importance of the indicators was determined using the Fuzzy Best–Worst Method (FBWM). In the next stage, a machine learning model based on the CatBoost algorithm was developed to classify the level of open innovation into four different categories. To improve the interpretability of the proposed model, the SHAP method was employed for sensitivity analysis and to investigate the contribution of each indicator to the model outputs. The results demonstrated that the proposed model achieved a prediction accuracy of 95% and a Macro-F1 score of 0.946, indicating a highly satisfactory performance in predicting open innovation levels. Furthermore, indicators such as top management support, innovation culture, organizational learning, and inter-organizational collaboration were identified as the most influential factors. The findings suggest that integrating multi-criteria decision-making methods, machine learning, and explainable artificial intelligence can provide an effective framework for supporting managerial decision-making in the field of open innovation.

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1) Introduction

In recent decades, the competitive environment of the food industry has become increasingly complex due to market globalization, rising customer expectations, sustainability requirements, and rapid technological advancements. Under such conditions, organizations can no longer rely solely on internal resources to create sustainable competitive advantages and are increasingly required to leverage external knowledge and technological capabilities (Shekarabi et al., 2024). In this context, open innovation has emerged as a modern managerial paradigm emphasizing knowledge interactions and inter-organizational collaboration throughout the supply chain. It enables organizations to enhance their performance and resilience through knowledge exchange, technological partnerships, and innovative networking (Barile et al., 2026). The importance of this approach is particularly evident in the food industry, where firms face challenges such as product perishability, demand fluctuations, food safety requirements, and logistical constraints, all of which intensify the need for continuous innovation (Gholian-Jouybari et al., 2024).

Despite the growing importance of open innovation, evaluating its level within supply chains remains a major challenge for both researchers and practitioners. Open innovation is a multidimensional and complex phenomenon influenced by various factors, including inter-organizational collaboration, knowledge management, technological infrastructure, organizational culture, and innovation performance (Lotfi et al., 2024; Molaei et al., 2025). Many previous studies have evaluated open innovation using traditional, static, and largely subjective approaches, while the relationships among innovation indicators are often nonlinear, dynamic, and context-dependent (Mashhadi et al., 2025; Yordudom et al., 2026). As a result, conventional models often lack sufficient capability to accurately analyze innovation systems and effectively support managerial decision-making.

From an academic perspective, evaluating open innovation in supply chains has become an important research area because it lies at the intersection of innovation management, supply chain strategy, digital transformation, and data-driven decision-making. Although open innovation has been widely discussed in the literature, there is still a need for more structured, quantitative, and interpretable evaluation models that can capture the complex relationships among organizational, technological, and collaborative factors. From an industrial perspective, this issue is particularly important for food supply chains, where firms must continuously respond to demand uncertainty, product perishability, food safety requirements, sustainability pressures, and intense market competition. In such an environment, the ability to assess the maturity and effectiveness of open innovation practices can help managers identify weaknesses, prioritize improvement actions, strengthen collaboration with external partners, and enhance supply chain competitiveness. Therefore, developing an explainable and data-driven decision support model for evaluating open innovation is valuable not only for advancing academic knowledge but also for supporting practical decision-making in the food industry.

In recent years, Multi-Criteria Decision-Making (MCDM) methods have received considerable attention for evaluating and prioritizing complex managerial indicators. Among these approaches, the Fuzzy Best–Worst Method (FBWM) has been recognized as an effective tool for weighting indicators due to its reduced number of pairwise comparisons, ability to handle

uncertainty in human judgments, and controlled inconsistency rate (Rostami et al., 2023; Sazvar et al., 2022). However, a significant portion of existing studies has limited the evaluation process to criteria weighting and has not utilized the capabilities of data-driven analysis and machine learning to identify hidden patterns and predict innovation levels. This research gap suggests that integrating MCDM methods with machine learning models can provide a more comprehensive and accurate framework for evaluating open innovation (Tajally et al., 2025; Vamarzani et al., 2026).

Alongside the development of data-driven approaches, machine learning algorithms have emerged as powerful tools for analyzing complex data and modeling nonlinear relationships (Khalili & Hamidi, 2021). Among these algorithms, CatBoost has become an effective method for classification problems due to its high accuracy, robustness against overfitting, and capability to model structured data (Rastgoo & Khajavi, 2023). Despite these advantages, one of the primary challenges of machine learning models is their black-box nature and the difficulty of interpreting their outputs for managers and decision-makers (Nessari et al., 2024). In response to this challenge, Explainable Artificial Intelligence (XAI) approaches have been developed, among which the SHAP algorithm is recognized as one of the most effective tools for analyzing the contribution and impact of variables. The use of SHAP makes it possible not only to predict the level of open innovation but also to transparently interpret the role of each indicator in the model's decisions.

A review of the literature indicates that although numerous studies have been conducted on open innovation, supply chains, and machine learning applications, there remains a significant gap in developing integrated frameworks based on the combination of MCDM, machine learning, and explainable artificial intelligence, particularly in the food industry where the unique characteristics of the sector increase the complexity of innovation evaluation. Most previous studies have either focused solely on conceptual analyses of open innovation, employed only MCDM approaches, or applied machine learning techniques without considering the relative importance of indicators and model interpretability. Therefore, the need for developing a data-driven and explainable decision support system for evaluating open innovation in the food supply chain has become increasingly evident.

Accordingly, the present study aims to develop an integrated framework based on FBWM, the CatBoost algorithm, and SHAP analysis for evaluating the level of open innovation in the food supply chain. In this study, key open innovation indicators are first identified and weighted; subsequently, the CatBoost algorithm is employed to classify organizations according to their open innovation level; and finally, SHAP analysis is used to identify the most influential factors affecting the model's performance. The main contribution of this research lies in integrating multi-criteria decision-making methods with machine learning models and explainable artificial intelligence approaches within a decision support system framework. This approach can not only improve evaluation accuracy but also provide valuable managerial insights for enhancing innovative performance in the food supply chain.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on open innovation evaluation, supply chain management, and data-driven decision support approaches. Section 3 presents the research methodology, including the dataset preparation procedure, FBWM-based indicator weighting, CatBoost classification model, and SHAP-based

explainability analysis. Section 4 reports and discusses the findings, including the weighting results, model performance evaluation, sensitivity analysis, and comparison with previous studies. Finally, Section 5 concludes the paper by summarizing the main findings, managerial implications, limitations, and future research directions.

2) Literature Review

To enhance the coherence of the review, the literature is organized thematically into three main research streams. The first stream includes studies focusing on the measurement and evaluation of open innovation and related innovation indicators. The second stream covers studies that examine the relationship between open innovation, organizational performance, and supply chain management. The third stream focuses on recent studies that integrate digital transformation, artificial intelligence, and data-driven approaches into innovation assessment. This thematic organization helps clarify the position of the present study within the existing literature and highlights the methodological and contextual gaps addressed in this research.

This section reviews previous studies related to open innovation evaluation and supply chain management. For instance, Mikhaylov et al. (2023) investigated the financial development factors affecting open innovation-oriented fintech potential in seven emerging economies. The study employed an integrated decision-making approach, including MF-X-DMA, regression analysis, M-SWARA, and ELECTRE based on bipolar q-ROFS fuzzy sets, using data from 2002 to 2020. The results indicated that capital market development, facilitation of bank lending, and equal access to financial information play significant roles in strengthening open innovation and fintech capacity development. Furthermore, the findings demonstrated that fuzzy multi-criteria decision-making approaches can serve as effective tools for analyzing innovation ecosystems and supporting economic policymaking in emerging economies. Carrasco-Carvajal et al. (2023) examined methods for measuring open innovation in small and medium-sized enterprises (SMEs) through a systematic literature review and bibliometric analysis. Their study analyzed 125 empirical articles published between 2009 and 2020 in the Web of Science and Scopus databases. The findings revealed that open innovation assessment utilizes diverse approaches, including internal and external knowledge flows, technology exploration and exploitation, inbound and outbound innovation, and organizational openness. The study emphasized that despite the conceptual richness of open innovation, the lack of standardized evaluation frameworks has made theoretical development and comparison of research findings difficult. Wang et al. (2023) explored the relationship between investment decisions, firm performance, and open innovation practices in Vietnam's wire and cable industry. Using Data Envelopment Analysis (DEA), including the Super-SBM model and the Malmquist index, the study evaluated the performance of the top ten wire and cable firms in Vietnam from 2017 to 2020. The findings showed that some firms demonstrated higher efficiency in innovation and productivity, while technological and technical gaps remained major barriers to industry growth. The results also indicated that integrating open innovation practices into investment decisions can improve financial performance, reduce costs, and increase profitability.

Similarly, Rumanti et al. (2023) examined the effects of business strategy, operational efficiency, and ownership structure on manufacturing performance under conditions of market uncertainty and competitive intensity. The research data were collected from manufacturing firms

listed on the Indonesia Stock Exchange between 2014 and 2021. The results demonstrated that aggressive business strategies, high operational efficiency, and foreign ownership positively and significantly influence manufacturing performance. Furthermore, organizations adopting open innovation approaches and flexible structures exhibited superior competitive performance under highly competitive conditions. Kurniawan et al. (2023) investigated the role of organizational creativity and open innovation in improving the performance of SMEs in Indonesia. Data were collected from 206 SMEs and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings revealed that both organizational creativity and open innovation positively and significantly affect organizational performance. Moreover, organizational creativity was conceptualized as a second-order construct comprising individual creativity, group creativity, internal environment, and knowledge creation, all of which contribute to strengthening organizational innovation capabilities and improving firm performance. Fuente-Ballesteros et al. (2025) introduced the Violet Innovation Grade Index (VIGI) as a novel survey-based metric for evaluating innovation in analytical methods. This model integrates ten criteria, including automation, interdisciplinarity, data processing, regulatory compliance, sensitivity, miniaturization, and advanced technologies. The proposed framework was applied in five analytical chemistry case studies, and the results showed that methods based on advanced technologies, automation, and intelligent data analysis demonstrated the highest innovation levels. The study highlighted the importance of developing multidimensional indicators for more accurate innovation assessment.

Moreira et al. (2025) evaluated digital transformation in SMEs using the Alkire-Foster method. In this study, partial and composite indicators were calculated to assess the level of digital technology integration within organizations, while linear regression analysis was employed to investigate factors affecting digital maturity. The results showed that although most firms possessed adequate digital infrastructure, they still faced challenges related to digital skills and workforce capabilities. The study demonstrated that multidimensional evaluation methods can effectively assess digital readiness and support digital transformation decision-making. A more recent stream of research has shifted attention toward the role of digital transformation, artificial intelligence, and data-driven analytical approaches in strengthening innovation capabilities (Taghizadeh et al., 2025). These studies are particularly relevant to the present research because they show how intelligent technologies can support innovation evaluation, ecosystem collaboration, and managerial decision-making. Barile et al. (2026) investigated the role of artificial intelligence as an enabler of open innovation within innovation ecosystems. Using the Lutech Campus case study, the research analyzed how an AI-based platform facilitates collaboration among companies, startups, universities, and other stakeholders. The findings revealed that AI-driven ecosystems can accelerate innovation processes, improve knowledge sharing, and strengthen sustainable value creation. The study further emphasized that AI-based analytics and process automation can significantly contribute to the development of sustainable innovation ecosystems and the achievement of ESG and SDG goals. Phrombutr et al. (2025) examined the relationships among absorptive capacity, AI literacy, algorithmic thinking skills, and open innovation competency among Generation Z entrepreneurship students in Thailand. Data were collected from 308 undergraduate students and analyzed using PLS-SEM. The findings indicated that absorptive capacity positively and

significantly influences AI literacy and algorithmic thinking skills, while these two variables play important mediating roles in developing open innovation competency. The results also demonstrated that algorithmic thinking skills are among the most critical success factors for open innovation in technology-driven and digital economy environments.

The reviewed studies indicate that open innovation has been examined from different perspectives, including measurement frameworks, organizational performance, digital transformation, and innovation ecosystem development. However, most prior studies have either relied on conceptual or statistical approaches, focused on general innovation contexts, or examined open innovation without integrating expert-based weighting, machine learning prediction, and explainable analysis in a unified framework. This shows that there is still a clear methodological and contextual gap in developing an interpretable, data-driven decision support model for evaluating open innovation specifically in the food supply chain.

Despite the considerable development of the literature, the review of previous studies reveals several important research gaps in the field of open innovation evaluation. First, many studies have either focused solely on identifying conceptual dimensions and indicators or relied on traditional evaluation and statistical analysis methods. Second, most existing studies have adopted static and non-intelligent approaches, paying limited attention to the capabilities of data-driven models and machine learning algorithms for analyzing complex innovation patterns. Third, in most studies, indicator weighting and predictive analysis have been conducted separately, while integrated frameworks capable of simultaneously considering criteria importance and nonlinear relationships among variables remain limited. Moreover, the interpretability of artificial intelligence models has often been neglected, and many proposed models lack the ability to provide transparent managerial insights. In addition, only a limited number of studies have specifically focused on the food industry and its supply chain, despite the complexity, sensitivity, and dynamic nature of this sector requiring more advanced analytical frameworks. Accordingly, the present study seeks to address part of the existing gap in the literature. The main contribution of this research lies in developing an integrated, data-driven, and explainable framework for evaluating open innovation in the food supply chain. In this study, the evaluation indicators are first weighted using a multi-criteria decision-making approach based on the FBWM method to scientifically determine the relative importance of each criterion. Subsequently, the CatBoost machine learning algorithm is employed to analyze the complex and nonlinear relationships among the indicators and predict the level of open innovation. Furthermore, the use of SHAP as an Explainable AI tool enables transparent interpretation of the model behavior and identification of the most influential factors affecting open innovation. The simultaneous integration of MCDM, machine learning, and explainable analysis within a decision support system framework represents the key novelty of this study, which can improve not only evaluation accuracy but also managerial applicability and strategic decision-making capability. Table 1 presents a summary and classification of the reviewed literature.

Table 1. Summary and Classification of the Literature Review

Author (Year)	Evaluation Indicators	Evaluation Model	Data-Driven	Case Study	Solution Method
Mikhaylov et al. (2023)	*	*	*	7 Emerging Economies	MF-X-DMA + M-SWARA + ELECTRE
Carrasco-Carvajal et al. (2023)	*			SMEs	Systematic Review + Bibliometric Analysis
Wang et al. (2023)	*	*	*	Vietnam Wire and Cable Industry	DEA (Super-SBM, Malmquist)
Aisyah et al. (2023)		*	*	Indonesian Manufacturing Firms	Statistical and Comparative Analysis
Kurniawan et al. (2023)	*	*	*	Indonesian SMEs	PLS-SEM
Fuente-Ballesteros et al. (2025)	*	*		Analytical Chemistry	VIGI Survey-Based Metric
Moreira et al. (2025)	*	*	*	SMEs	Alkire-Foster + Regression
Barile et al. (2025)	*	*	*	Lutech Campus Ecosystem	AI-Based Case Study
Phrombutr et al. (2025)	*	*		Thai Entrepreneurship Students	PLS-SEM
Present Study	*	*	*	Food Supply Chain	FBWM – CatBoost – SHAP

3) Methodology

In this study, an integrated approach combining multi-criteria decision-making methods, machine learning, and explainable analysis was employed to develop a data-driven and explainable framework for evaluating open innovation in the food supply chain. In the first stage, open innovation evaluation indicators were identified and finalized based on a comprehensive literature review and previous studies. Subsequently, the Fuzzy Best–Worst Method (FBWM) was applied to determine the relative importance of the indicators and reduce uncertainty in expert judgments. The output of this stage consisted of the final weights of the open innovation indicators, which were later used as the basis for the data-driven analysis. After weighting the indicators, a structured dataset including the evaluation indicators and different levels of open innovation was developed to enable the implementation of the machine learning model.

In the next stage, the CatBoost algorithm was employed as the main classification model to predict the level of open innovation in the supply chain. The dataset was divided into training and testing subsets, and the model parameters were optimized to achieve the best predictive performance. The model performance was then evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score. To enhance the transparency and interpretability of the model, the SHAP algorithm was utilized for sensitivity analysis and to examine the contribution of each indicator to the model outputs. This analysis enabled the identification of the most influential factors affecting the level of open innovation and provided valuable managerial insights. Figure 1

illustrates the research flowchart and presents the implementation stages of the proposed framework step by step.

The methodological approaches used in this study were selected based on the nature of the research problem and the need to combine expert judgment, predictive modeling, and interpretability. FBWM was applied because open innovation evaluation involves multiple qualitative and quantitative indicators, and this method can determine criteria weights with fewer pairwise comparisons while handling uncertainty in expert judgments. CatBoost was selected as the main machine learning algorithm due to its strong performance on structured datasets, ability to capture nonlinear relationships among indicators, and robustness against overfitting. Finally, SHAP was used because predictive accuracy alone is not sufficient for managerial decision-making; decision-makers also need to understand how each indicator contributes to the predicted level of open innovation. Therefore, the integration of FBWM, CatBoost, and SHAP provides a suitable framework for weighting, prediction, and explanation within a unified decision support model.

a. Dataset Preparation and Privacy-Preserving Anonymization Procedure

The dataset used in this study was prepared based on organizational evaluation data, collected from several large food companies operating in Iran. The original data reflected the assessment of open innovation practices across the finalized 34 indicators, covering dimensions such as inter-organizational collaboration, knowledge management, technological infrastructure, organizational culture, innovation process management, and innovation performance outcomes. However, due to confidentiality restrictions and the sensitivity of company-level information, the original organizational records could not be directly reported or publicly disclosed. Therefore, a privacy-preserving anonymization procedure was applied to prepare the final dataset while maintaining the main statistical, structural, and managerial characteristics of the original observations.

The purpose of this procedure was not to generate a purely artificial dataset, but to develop an anonymized and confidentiality-preserving version of the original organizational data. In this process, company identifiers and sensitive information were removed, and limited controlled transformations were applied to the original numerical values. These transformations were designed to protect the identity of the participating companies while preserving the empirical ranges, relative variations, and general relationships among the indicators. Therefore, the final dataset can be considered a privacy-preserving organizational dataset derived from real company-level evaluations rather than a fully synthetic dataset generated without empirical basis. The dataset preparation process is summarized as follows:

Input: Original organizational evaluation records based on 34 open innovation indicators

Output: An anonymized dataset for machine learning model development

Step 1: Collect organizational evaluation records from several large food companies based on the finalized open innovation indicators

Step 2: Remove company identifiers, direct organizational names, and any sensitive information that could reveal the identity of participating firms

Step 3: Check the completeness and consistency of the 34 indicator values across all organizational records

Step 4: Normalize the indicator values to ensure comparability across different measurement scales

Step 5: Apply limited controlled perturbations to sensitive numerical values to preserve confidentiality

Step 6: Preserve the empirical ranges, relative variations, and distributional patterns observed in the original organizational data

Step 7: Maintain the relationships among indicators by applying transformations at the record level rather than independently generating each feature

Step 8: Assign open innovation levels based on the overall evaluation structure and expert-validated indicator patterns

Step 9: Review the final anonymized dataset to ensure consistency with expected theoretical patterns reported in the open innovation literature

Step 10: Use the final anonymized dataset for training, testing, comparison, and the interpretation of the machine learning models

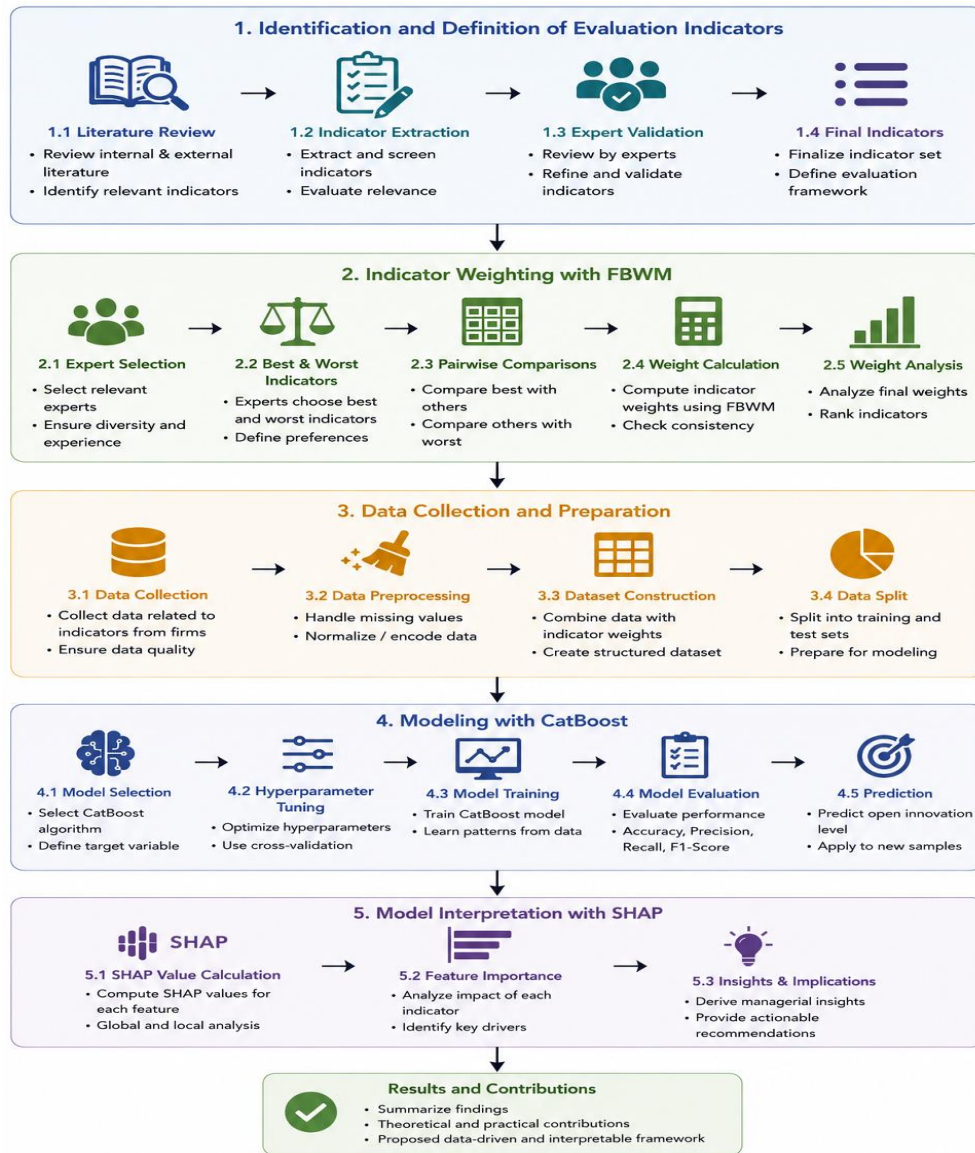


Figure 1. Research Flowchart

Regarding distributional assumptions, the values of the indicators were not generated from arbitrary theoretical distributions. Instead, the final dataset was prepared by relying on the empirical patterns observed in the original organizational data. Accordingly, the range and variation of each indicator were preserved as much as possible. The privacy-preserving transformations were applied within limited boundaries so that the overall structure of the original data remained stable. This approach reduced the risk of producing unrealistic observations and helped maintain the practical relevance of the dataset for evaluating open innovation in food supply chains.

In addition, the correlation structure among the 34 indicators was considered during the anonymization process. Since open innovation indicators are theoretically interrelated, independently generating or modifying each indicator could distort meaningful relationships among variables. For example, indicators such as top management support, organizational innovation culture, organizational learning, inter-organizational collaboration, knowledge sharing, and supply chain performance improvement are expected to show logical associations. Therefore, controlled transformations were applied at the record level to preserve the overall relationships among indicators and avoid unrealistic combinations of values.

To further examine the reliability of the prepared dataset, sensitivity checks were conducted by slightly varying the intensity of the anonymization transformations. The results showed that the overall class distribution, the relative importance of key indicators, and the general performance pattern of the machine learning models remained stable under limited changes in the transformation parameters. This indicates that the results were not highly sensitive to minor changes in the anonymization procedure. Furthermore, the final patterns observed in the dataset were compared with expected patterns from the open innovation literature. The higher influence of managerial support, innovation culture, organizational learning, knowledge sharing, and inter-organizational collaboration was consistent with prior theoretical and empirical findings, supporting the validity of the prepared dataset for the purpose of this study.

b. Fuzzy Best–Worst Method

The Fuzzy Best–Worst Method (FBWM) is a multi-criteria decision-making approach used to determine criteria weights under uncertainty and linguistic expert judgments. By integrating fuzzy logic with pairwise comparisons, this method enables the calculation of indicator weights with higher consistency and fewer comparisons (Nayeri et al., 2023).

In this study, experts first identified the best and worst indicators. Subsequently, fuzzy pairwise comparisons were conducted between the best indicator and other indicators, as well as between the remaining indicators and the worst indicator. The final weights of the criteria were then calculated using the FBWM model, and the consistency ratio of the results was evaluated.

The primary advantage of FBWM is the reduction in the number of pairwise comparisons while improving the accuracy and consistency of results compared to traditional MCDM methods. Furthermore, the integration of fuzzy logic allows for more effective handling of uncertainty and ambiguity in human judgments (Alavi et al., 2021; Guo & Zhao, 2017).

c. Categorical Boosting

The Categorical Boosting (CatBoost) algorithm is an advanced gradient boosting-based machine learning algorithm that performs effectively in structured data analysis and classification problems. By sequentially training multiple decision trees, this algorithm gradually minimizes prediction errors and develops an accurate predictive model. Due to its strong capability in modeling nonlinear relationships, resistance to overfitting, and robust performance on medium-sized datasets, CatBoost was selected as the main model in this study (Zeynali et al., 2025).

In this research, a dataset including 34 open innovation evaluation indicators and a target variable was first prepared and divided into training and testing subsets. The problem was then defined as a multiclass classification task involving four levels of open innovation. Next, the indicator weights obtained from the FBWM method were incorporated into the model as feature weights to enhance the importance of key indicators during the learning process. Subsequently, the model parameters, including Iterations, Depth, Learning Rate, and L2 Regularization, were optimized using the Grid Search method, and the CatBoost model was trained on the training dataset. Finally, the model performance was evaluated using Accuracy, Precision, Recall, and F1-Score metrics, while model interpretability analysis was conducted using the SHAP method.

The use of the CatBoost algorithm in this study offers several advantages. The algorithm demonstrates strong capability in analyzing complex and nonlinear relationships among open innovation indicators and provides greater stability and predictive accuracy compared to many similar algorithms (Qian et al., 2023). In addition, the integration of feature weights derived from FBWM improved prediction quality, while the interpretability of the model through SHAP enabled the extraction of managerial insights and identification of the most influential indicators (GhanavatiNejad et al., 2025).

d. Shapley Additive Explanations

The Shapley Additive Explanations (SHAP) algorithm is an advanced explainability approach for machine learning models developed based on game theory and used to analyze the contribution of each feature to model predictions. By employing Shapley values, this method determines both the magnitude and direction of the impact of each indicator on the model output and enables the interpretation of complex black-box models such as CatBoost (Nessari et al., 2024).

In this study, the final trained CatBoost model was first selected as the input for SHAP analysis. Then, using the TreeExplainer algorithm, SHAP values were calculated for all samples and indicators. Since the research problem was defined as a multiclass classification task, SHAP analysis was conducted separately for each level of open innovation. Subsequently, Summary Plot visualizations were generated to illustrate the magnitude and direction of the impact of indicators on the model output. Furthermore, the overall importance of each indicator was determined using the mean absolute SHAP values, enabling the identification of the most influential factors affecting the prediction of open innovation levels.

The use of SHAP significantly improved the transparency and interpretability of the machine learning model in this study. In addition to providing a global interpretation of model behavior, this method also enables local analysis of feature impacts at the individual sample level, which is highly valuable for managerial insight extraction and sensitivity analysis (Jabeur et al., 2024). Moreover, the strong compatibility of SHAP with tree-based models such as CatBoost and

its high accuracy in feature contribution analysis make it an effective tool for explaining model outcomes.

Discussion and Findings

This section presents and analyzes the results obtained from weighting open innovation indicators using the FBWM method, developing the data-driven CatBoost model, and evaluating the model performance. Furthermore, the SHAP method is employed to investigate the impact and importance of each indicator in predicting the level of open innovation in the food supply chain.

a. Indicator Weighting

After identifying and finalizing the open innovation evaluation indicators, the relative weights and importance of each dimension and indicator were determined using the FBWM method. The objective of this stage was to identify the influence level of each indicator within the open innovation evaluation model for the food supply chain industry. For this purpose, an FBWM-based expert questionnaire was distributed among 15 experts in the fields of food industry, information technology, and supply chain management. The expert panel consisted of three main groups: senior managers from large food industry companies, consultants and practitioners with practical experience in food supply chain management, and academic researchers and university professors specializing in food industry studies, innovation management, and open innovation. The inclusion of these three groups was intended to ensure that the weighting process reflected both practical industry knowledge and academic expertise. The experts were selected based on their professional experience, familiarity with food supply chain processes, and knowledge of innovation-related decision-making in organizational contexts. Based on the experts' judgments, the weights of the main dimensions, internal indicator weights, and final weights of each indicator were calculated.

The results of the indicator weighting process are presented in Table 2. According to the findings, among the main dimensions, "Inter-organizational Collaboration and Interactions" obtained the highest weight (0.1923). This was followed by "Knowledge Management and Sharing" with a weight of 0.1809 and "Open Innovation Performance and Outcomes" with a weight of 0.1741. These results indicate that, from the experts' perspective, the success of open innovation in the food supply chain primarily depends on the quality of inter-organizational interactions, effective knowledge flow, and innovation performance outcomes.

Table 2. Final Weighting of Open Innovation Evaluation Indicators Using the FBWM Method

Category	Category Weight	Indicator	Internal Weight	Final Weight
Inter-organizational Collaboration and Interactions	0.1923	Collaboration with Suppliers	0.1675	0.0322
		Collaboration with Customers	0.1530	0.0294
		Collaboration with Research Centers and Universities	0.1328	0.0255
		Supply Chain Networking Level	0.1270	0.0244
		Intensity of Inter-organizational Interactions	0.1203	0.0231
		Inter-organizational Trust	0.1684	0.0324
		Organizational Readiness for Open Collaboration	0.1309	0.0252
Knowledge Management and Sharing	0.1809	Internal Knowledge Sharing	0.1426	0.0258
		External Knowledge Sharing	0.1593	0.0288
		External Knowledge Absorptive Capacity	0.2016	0.0365

Table 2. Final Weighting of Open Innovation Evaluation Indicators Using the FBWM Method

Category	Category Weight	Indicator	Internal Weight	Final Weight
		Organizational Knowledge Management	0.1750	0.0317
		Knowledge Sharing Culture	0.1455	0.0263
		Information Flow Transparency	0.1760	0.0318
Technological Infrastructure and Capabilities	0.1713	Use of Digital Technologies	0.1798	0.0308
		IT and Information Infrastructure	0.1633	0.0280
		Adoption of Advanced Technologies	0.1691	0.0290
		Information Systems Integration	0.1769	0.0303
		Data Security and Information Confidentiality	0.1448	0.0248
		Supply Chain Traceability and Transparency	0.1662	0.0285
Organizational Culture and Structure	0.1292	Top Management Support for Innovation	0.3653	0.0472
		Organizational Innovation Culture	0.3447	0.0445
		Organizational Learning Level	0.2901	0.0375
Innovation Processes and Management	0.1522	Formal Innovation Processes	0.1696	0.0258
		Idea Management	0.1628	0.0248
		Collaborative Product Development	0.1851	0.0282
		Innovation Process Integration	0.1657	0.0252
		Innovation Evaluation and Monitoring	0.1599	0.0243
		Innovation Process Agility	0.1570	0.0239
Open Innovation Performance and Outcomes	0.1741	Innovative Project Success	0.1649	0.0287
		Supply Chain Performance Improvement	0.1905	0.0332
		Supply Chain Flexibility Improvement	0.1754	0.0305
		Customer Satisfaction Improvement	0.1412	0.0246
		Competitive Advantage from Innovation	0.1791	0.0312
		Waste Reduction and Sustainability Improvement	0.1488	0.0259

At the indicator level, “Top Management Support for Innovation,” with a final weight of 0.0472, was identified as the most important indicator. In addition, “Organizational Innovation Culture” (0.0445), “Organizational Learning Level” (0.0375), and “External Knowledge Absorptive Capacity” (0.0365) received the highest weights. These findings indicate that managerial, cultural, and organizational learning factors play a fundamental role in the development of open innovation. Furthermore, within the dimension of inter-organizational collaboration and interactions, the indicators “Inter-organizational Trust” and “Collaboration with Suppliers” achieved the highest importance, highlighting the critical role of trust and sustainable collaboration in knowledge exchange and joint project implementation within the food supply chain.

To evaluate the validity and consistency of expert judgments, inconsistency ratios were calculated for different levels of the model. The results indicated that the overall inconsistency ratio of the model was 0.024, which is considered a very low value and demonstrates a satisfactory level of consistency in expert judgments during the weighting process. Moreover, the inconsistency ratios for all major dimensions were within acceptable ranges. Among them, the “Inter-organizational Collaboration and Interactions” dimension exhibited the lowest inconsistency ratio (0.011), indicating a very high level of agreement among experts regarding the importance of indicators in this dimension. This was followed by “Knowledge Management and Sharing” and “Technological Infrastructure and Capabilities” with inconsistency ratios of 0.014 and 0.015, respectively,

reflecting high consistency levels. The inconsistency ratio for “Organizational Culture and Structure” was 0.019, while “Innovation Processes and Management” recorded a value of 0.034, both of which remained within acceptable limits. The highest inconsistency ratio belonged to the “Open Innovation Performance and Outcomes” dimension with a value of 0.047; however, this value was still relatively low and indicated an acceptable logical consistency in expert judgments. Overall, the low inconsistency ratios across all dimensions confirm the reliability and validity of the extracted weights and demonstrate that they can be effectively used as reliable inputs for developing the machine learning model in the next stage of the study.

b. Open Innovation Evaluation Model for the Food Supply Chain

In this section, a data-driven machine learning model was developed to assess and classify the level of open innovation in the food supply chain. Unlike traditional approaches, which are mainly based on descriptive analysis and multi-criteria decision-making, machine learning models are capable of identifying hidden patterns and nonlinear relationships among indicators and can therefore provide more accurate predictions of open innovation status. In this study, using the final indicators extracted and weighted through the FBWM method, a multiclass classification framework was designed to predict the level of organizational open innovation across four different categories.

To train and evaluate the model, a dataset containing 400 records was created, where each record represented an organization or decision-making unit within the food supply chain. The dataset used in this study was constructed based on real evaluation data collected from several large food companies operating in Iran. However, due to confidentiality restrictions and the sensitivity of organizational information, the original data could not be directly disclosed. Therefore, the dataset was anonymized and slightly transformed to preserve the statistical characteristics of the original observations while preventing the identification of the participating companies. In this process, the range, relative variation, and relationships among the indicators were maintained as much as possible, and controlled perturbations were applied to sensitive values. Accordingly, the final dataset can be considered a privacy-preserving, semi-synthetic dataset derived from real organizational data rather than a purely simulated dataset generated without empirical basis. The dataset included 34 final indicators as input features, covering various dimensions of open innovation, including inter-organizational collaboration, knowledge management, technological infrastructure, organizational culture, innovation processes, and innovation performance. The target variable was defined as a multiclass variable with four levels: “Low Open Innovation,” “Moderate Open Innovation,” “Good Open Innovation,” and “Advanced Open Innovation.” Figure 2 illustrates the distribution of dataset labels.

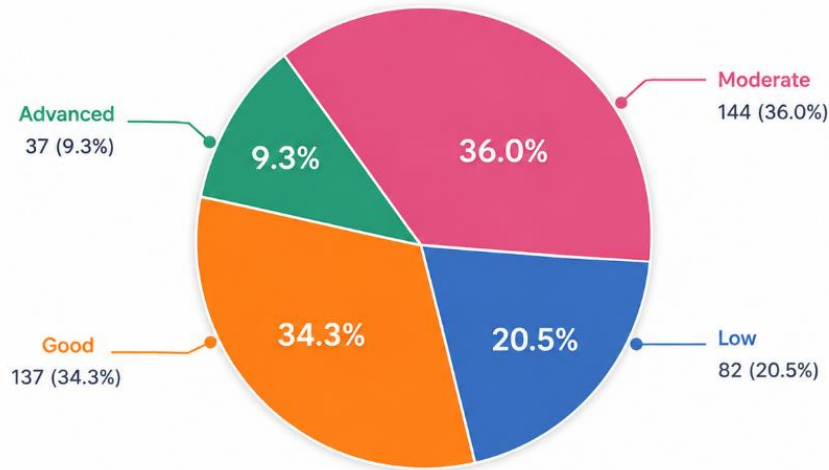


Figure 2. Distribution of Dataset Labels

The label distribution analysis indicated that the majority of data belonged to the “Moderate Open Innovation” and “Good Open Innovation” classes, while the “Advanced Open Innovation” class contained the fewest samples. Nevertheless, the class distribution exhibited an acceptable level of balance, enabling the development of a reliable and generalizable model. In the modeling stage, the CatBoost algorithm was selected as the primary classification model. The main reasons for choosing this algorithm were its strong capability in analyzing nonlinear relationships, its effective performance in multiclass classification problems, and its ability to incorporate feature weights during the learning process. In this study, the final indicator weights, obtained from the FBWM stage, were integrated into the model as feature weights so that more important indicators could play a stronger role during model training. To optimize the model performance, parameter tuning was conducted using the Grid Search method. In this process, several combinations of key model parameters, including Iterations, Depth, Learning Rate, and L2 Leaf Regularization, were evaluated, and the best combination was selected based on the Macro-F1 criterion.

Table 3. Grid Search Results for CatBoost Parameter Tuning

No.	Iterations	Depth	Learning Rate	L2 Leaf Reg	Mean CV Macro-F1	Std CV Macro-F1
1	60	6	0.08	3	0.9311	0.0401
2	120	6	0.08	3	0.9302	0.0349
3	120	4	0.08	3	0.9268	0.0627
4	60	4	0.08	3	0.9185	0.0617

Based on the results, the best parameter combination included: Iterations = 60, Depth = 6, Learning Rate = 0.08, and L2 Leaf Regularization = 3, which achieved the highest Macro-F1 value during cross-validation.

Subsequently, the dataset was divided into training and testing subsets, where 80% of the data were used for training and 20% for testing. Due to the multiclass nature of the target variable, the model loss function was defined as MultiClass. After training the model, its performance was evaluated using several metrics, including Accuracy, Balanced Accuracy, Precision, Recall, Macro-F1, and Weighted-F1.

Table 4. Evaluation Metrics of the CatBoost Model

Evaluation Metric	Value
Accuracy	0.9500
Balanced Accuracy	0.9378
Macro Precision	0.9593
Macro Recall	0.9378
Macro F1	0.9468
Weighted F1	0.9497

The results demonstrated that the CatBoost model achieved an overall prediction accuracy of 95% in classifying open innovation levels. Furthermore, the Macro-F1 value of 0.9468 and Balanced Accuracy of 0.9378 indicate that the model performed consistently across all classes. These findings suggest that the model was not merely influenced by the frequency of dominant classes and was able to accurately identify all levels of open innovation.

To further investigate the model performance across different open innovation levels, a classification report including Precision, Recall, and F1-score for each class was generated, as presented in Table 5.

Table 5. Classification Report of the CatBoost Model

Open Innovation Level	Precision	Recall	F1-score	Support
Advanced Open Innovation	1.00	0.86	0.92	7
Good Open Innovation	0.93	0.96	0.95	27
Low Open Innovation	0.94	1.00	0.97	17
Moderate Open Innovation	0.96	0.93	0.95	29
Accuracy			0.95	80
Macro Average	0.96	0.94	0.95	80
Weighted Average	0.95	0.95	0.95	80

According to the results, the model achieved its best performance in identifying the “Low Open Innovation” class, with a Recall value of 1.00. In addition, for the “Advanced Open Innovation” class, the Precision value reached 1.00, indicating that all samples classified by the model as advanced were correctly identified. The model also demonstrated highly satisfactory performance in the “Good” and “Moderate” classes, where the F1-score for both classes was approximately 0.95. Furthermore, the Macro-F1 value of 0.9468 and Balanced Accuracy of 0.9378 indicate that the model performed consistently across all classes. These findings suggest that the model was not merely influenced by the frequency of dominant classes and was able to accurately identify all levels of open innovation.

In addition to statistical metrics, the discriminative power of the model was evaluated using a multiclass ROC curve, as illustrated in Figure 3. In this analysis, the AUC values for the different classes ranged between 0.99 and 1.00, while the Micro-average AUC reached 1.00, demonstrating the excellent capability of the model in distinguishing among different open innovation levels.

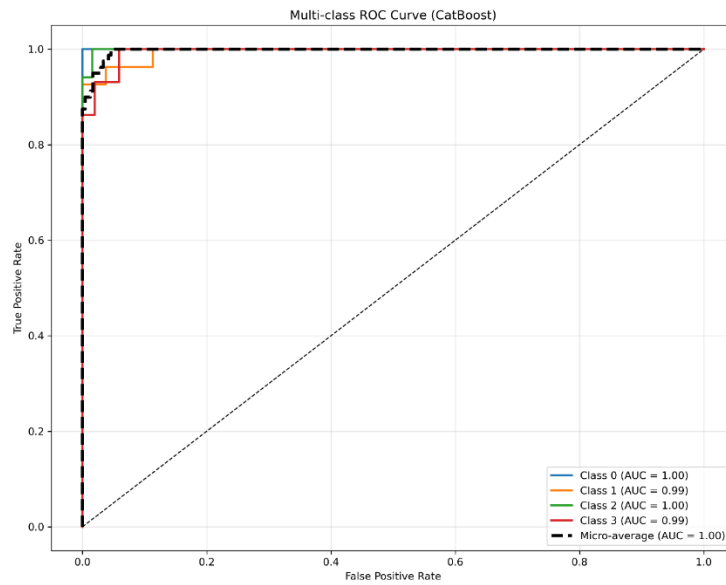


Figure 3. Multiclass ROC Curve of the CatBoost Model for Open Innovation Level Classification

Overall, the results obtained from the evaluation metrics, classification report, and ROC analysis indicate that the developed CatBoost model possesses high accuracy, stability, and discriminative capability. Therefore, it can be effectively utilized as a data-driven decision support system for evaluating the level of open innovation in the food supply chain. Furthermore, the integration of FBWM-derived weights with the nonlinear learning capability of CatBoost has provided an effective framework for analyzing and predicting open innovation status.

c. Model Performance Evaluation

To evaluate the effectiveness of the proposed model, its performance was compared with several commonly used machine learning algorithms, including standard CatBoost, Random Forest, Artificial Neural Network (ANN), and Support Vector Machine (SVM). In all models, the same data partitioning strategy was applied, consisting of 80% training data and 20% testing data. The evaluation metrics included Accuracy, Precision, Recall, and F1-Score, as presented in Table 6.

Table 6. Performance Comparison of the Proposed Model with Different Machine Learning Algorithms

Model	Accuracy	Precision	Recall	F1-Score
CatBoost + FBWM	0.950	0.959	0.938	0.947
CatBoost	0.932	0.938	0.921	0.928
XGBoost	0.927	0.933	0.918	0.924
LightGBM	0.921	0.929	0.912	0.919
Random Forest	0.915	0.922	0.904	0.910
Neural Network (ANN)	0.901	0.908	0.892	0.897
Support Vector Machine (SVM)	0.884	0.890	0.873	0.879

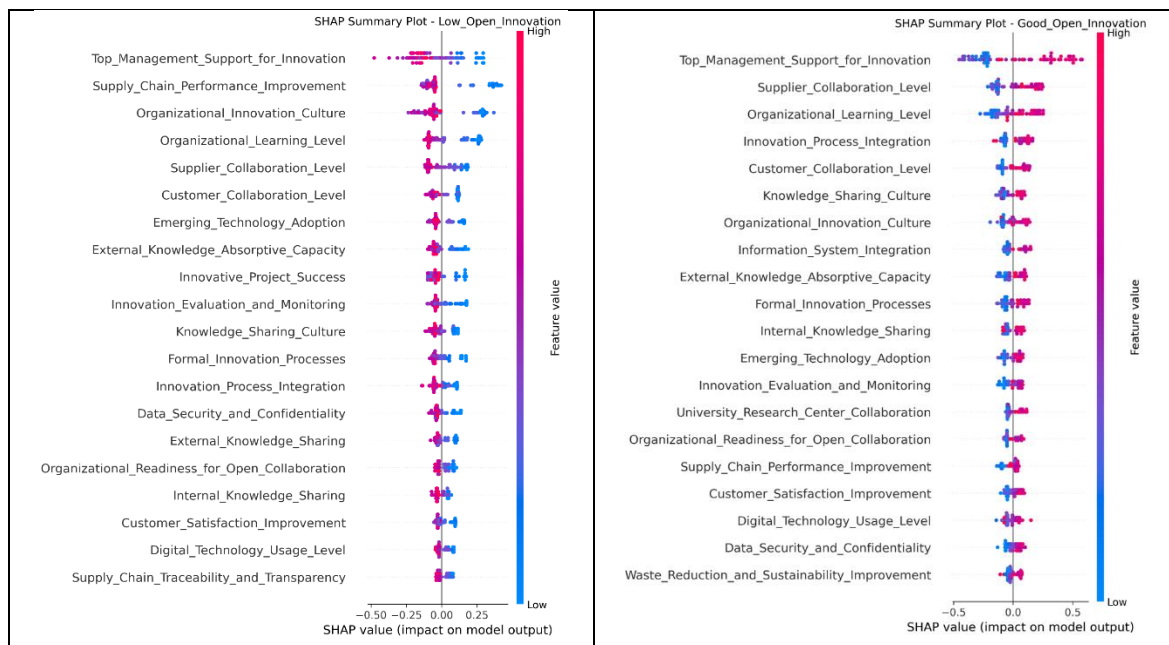
The results indicate that the proposed model based on CatBoost integrated with FBWM weights achieved the best performance across all evaluation metrics. The model obtained an Accuracy of 0.950 and an F1-Score of 0.947, demonstrating both high predictive accuracy and balanced classification performance across all classes. Furthermore, comparison with the standard

CatBoost model revealed that incorporating the FBWM-derived feature weights improved the overall model performance and significantly enhanced prediction accuracy.

Although the dataset did not include categorical input features, CatBoost was selected due to its ordered boosting mechanism, strong regularization capability, stability on medium-sized structured datasets, and competitive performance compared with other gradient boosting algorithms, such as XGBoost and LightGBM. The empirical comparison in Table 6 shows that the proposed CatBoost + FBWM model achieved the best overall performance across all evaluation metrics. On the other hand, the Random Forest, ANN, and SVM algorithms also produced acceptable results; however, they exhibited lower accuracy and discriminative capability compared to the proposed model. These findings demonstrate that integrating feature weighting with the CatBoost algorithm provides a more accurate and intelligent framework for evaluating the level of open innovation in the food supply chain.

d. Sensitivity Analysis Using SHAP

To enhance the interpretability of the proposed model and examine the influence of different indicators on prediction results, SHAP-based sensitivity analysis was employed. This method enables the analysis of the contribution of each input variable to the prediction of different open innovation levels and illustrates the magnitude and direction of each indicator's effect on the model output. Unlike traditional feature importance approaches, SHAP can analyze model behavior separately for each class, thereby providing a more detailed understanding of the model's decision-making process. The outputs of the SHAP algorithm are presented in Figure 4.



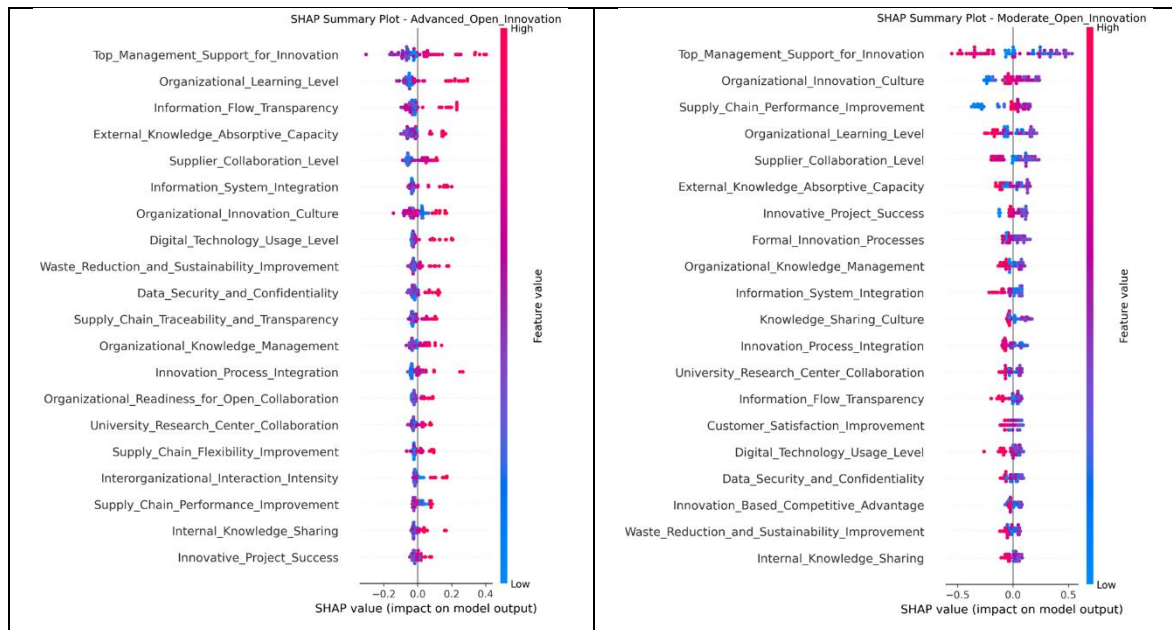


Figure 4. SHAP-Based Sensitivity Analysis of the CatBoost Model for Different Levels of Open Innovation

The SHAP analysis revealed that indicators such as “Top Management Support for Innovation,” “Organizational Innovation Culture,” “Organizational Learning Level,” and “Supply Chain Performance Improvement” were among the most influential factors across all levels of open innovation. In the “Low Open Innovation” class, higher values of these indicators negatively affected the probability of belonging to this class, whereas in the “Advanced Open Innovation” class, the same indicators had a strong positive effect on the model output. These findings demonstrate the consistency of the model results with the theoretical foundations of open innovation and confirm the logical behavior of the machine learning model. Furthermore, the results showed that in the “Moderate Open Innovation” level, the effects of the indicators were more balanced, with a wider distribution around the zero value, reflecting the intermediate condition of organizations in this category. In the “Good Open Innovation” level, indicators such as supplier collaboration, organizational learning, and the integration of innovation processes played a more prominent role. Overall, the SHAP analysis demonstrated that the proposed model not only provides high predictive accuracy but also offers strong interpretability, enabling the extraction of valuable managerial insights regarding the key success factors of open innovation in the food supply chain.

Comparative Discussion with Previous Studies

To further clarify the contribution of the proposed framework, this subsection compares the present study with the closest existing studies in the field of open innovation evaluation, innovation performance assessment, and data-driven decision support. Although previous studies have provided valuable insights into open innovation measurement, organizational performance, digital transformation, and innovation ecosystems, most of them have focused on either conceptual evaluation, statistical analysis, multi-criteria decision-making, or case-based investigation. In contrast, the present study integrates expert-based indicator weighting, machine learning-based

classification, and explainable artificial intelligence within a unified decision support framework for evaluating open innovation in the food supply chain.

Table 7. Comparative Analysis of the Proposed Framework with Relevant Existing Studies

Study	Context	Indicator Weighting	Data-Driven Prediction	Explainable AI	Food Supply Chain Focus	Main Difference from the Present Study
Mikhaylov et al. (2023)	Open innovation-oriented fintech potential	Yes	No	No	No	Focused on macro-level fintech potential but did not develop an explainable machine learning framework for organizational-level open innovation evaluation
Carrasco-Carvajal et al. (2023)	Open innovation measurement in SMEs	No	No	No	No	Reviewed measurement approaches but did not propose a predictive decision support model
Wang et al. (2023)	Innovation and performance evaluation	No	No	No	No	Used performance evaluation methods without integrating expert weighting, machine learning, and explainability
Kurniawan et al. (2023)	Open innovation and SME performance	No	No	No	No	Examined causal relationships using statistical modeling but did not classify open innovation levels
Moreira et al. (2025)	Digital transformation in SMEs	No	Partly	No	No	Focused on digital maturity and regression-based analysis rather than explainable open innovation evaluation
Barile et al. (2026)	AI-enabled open innovation ecosystem	No	Partly	No	No	Provided case-based insights into AI-enabled innovation ecosystems but did not offer a quantitative classification framework
Phrombutr et al. (2025)	Open innovation competency	No	No	No	No	Investigated open innovation competency using PLS-SEM without integrating MCDM, ML, and XAI
Present Study	Open innovation in food supply chains	Yes, FBWM	Yes, CatBoost	Yes, SHAP	Yes	Integrates expert-based weighting, machine learning classification, and explainable AI for decision support

As shown in Table 7, the closest existing studies have addressed different aspects of open innovation, including measurement, performance evaluation, digital transformation, and ecosystem development. However, they have not combined indicator weighting, predictive modeling, and

explainable analysis in a single framework. The present study contributes to the literature by linking FBWM-based expert knowledge with CatBoost-based classification and SHAP-based interpretation. This integration enables not only the prediction of open innovation levels but also the identification of the most influential managerial and organizational factors. Therefore, the proposed framework extends previous studies by offering a more comprehensive, interpretable, and decision-oriented approach for evaluating open innovation in food supply chains.

Managerial Insights

The findings of this study provide several practical insights for managers in the food supply chain. First, the results show that open innovation should not be treated only as a technological issue, but as a managerial and organizational capability. The high importance of top management support, organizational innovation culture, and organizational learning indicates that managers should begin by strengthening internal readiness for innovation. This means that senior managers need to actively support collaborative innovation projects, allocate resources to innovation-related activities, encourage knowledge sharing among employees, and create an organizational culture that accepts external ideas, experimentation, and continuous improvement. Without such internal readiness, investments in digital technologies or external partnerships may not lead to effective open innovation outcomes.

Second, the results highlight the importance of inter-organizational collaboration and knowledge exchange across the food supply chain. Managers should therefore establish structured mechanisms for collaboration with suppliers, customers, research centers, universities, and technology partners. Practical actions may include joint product development projects, supplier innovation programs, shared data platforms, collaborative problem-solving sessions, and formal channels for capturing external knowledge. In addition, the SHAP analysis can help managers identify which indicators have the strongest impact on the predicted level of open innovation in their organization. As a result, the proposed decision support framework can be used not only for assessment but also for prioritizing improvement actions, benchmarking organizational innovation maturity, and designing targeted strategies to enhance competitiveness, sustainability, and innovation performance in food supply chains.

Conclusion

This study developed an integrated, data-driven, and explainable decision support framework for evaluating the level of open innovation in the food supply chain. To achieve this objective, key open innovation indicators were first identified through a review of the literature and expert opinions, and their relative importance was determined using the Fuzzy Best-Worst Method. The weighting results showed that inter-organizational collaboration, knowledge management, innovation performance, top management support, organizational innovation culture, and organizational learning are among the most influential factors in assessing open innovation. In the next stage, the CatBoost algorithm was employed to classify the level of open innovation across four categories. The results indicated that integrating expert-based indicator weights with the CatBoost model improved the predictive performance of the framework compared with the standard CatBoost model and other machine learning algorithms. Furthermore, SHAP analysis enhanced the interpretability of the model by identifying the contribution of each indicator to different levels of

open innovation. Therefore, the proposed framework provides both predictive capability and managerial interpretability, which are essential for supporting decision-making in complex supply chain environments.

The findings of this study suggest that combining multi-criteria decision-making, machine learning, and explainable artificial intelligence can offer a practical and structured approach for evaluating open innovation in the food industry. From a managerial perspective, the proposed framework can help decision-makers identify innovation strengths and weaknesses, prioritize improvement actions, strengthen collaboration with external partners, and enhance knowledge-sharing and technological capabilities across the supply chain. Nevertheless, this study has some limitations. The dataset was derived from organizational data collected from several large food companies and was anonymized and slightly transformed to preserve confidentiality; therefore, future studies are encouraged to validate the proposed framework using larger real-world datasets from different industries and organizational contexts. In addition, although the proposed model achieved the best performance in the present experimental setting, the relatively limited test sample size suggests that future research should employ repeated validation procedures and statistical significance tests to further examine the robustness of performance differences among competing models. Future studies may also extend the framework by incorporating longitudinal data, hybrid optimization approaches, and advanced learning algorithms to analyze the dynamic evolution of open innovation capabilities over time.

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