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Artificial Intelligence-Based Assessment of Industrial Transformation Pathways in Iran's Food Industry

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Abstract

The development of non-oil exports has become a strategic priority for Iran due to vulnerability associated with oil dependence and the need for sustainable economic growth. Within this framework, the food manufacturing sector, as a key component of the agricultural value chain, possesses considerable potential for value creation, employment generation, and integration into regional and global markets. However, despite significant production capacities and geographical advantages, Iran's food industry has not fully achieved its export potential, highlighting the need for effective industrial transformation pathways. This study develops an artificial intelligence-based framework to assess transformation pathways in Iran's food industry by integrating historical evidence with expert knowledge. Machine learning models, including Random Forest and XGBoost, were applied using annual time-series data from 2000 to 2022 to identify major determinants of food industry export performance. The predictive results were interpreted through Explainable Artificial Intelligence (SHAP) to reveal the contribution and direction of influential factors. Furthermore, an expert-based Self-Organizing Map (SOM) clustering approach was employed using perceptions of 150 industrial experts to identify feasible transformation priorities. The results indicate that variables associated with food manufacturing capacity, industrial productivity, and agricultural value creation provide the largest contributions to the predictive structure of food export performance, while the exchange rate represents an important but comparatively lower-ranked factor. The expert-based analysis, however, identifies exchange rate instability, policy uncertainty, and weak international market capabilities as major institutional and strategic constraints affecting the practical realization of export potential.

Keywords: Artificial Intelligence; Food Industry; Machine Learning.

چکیده

توسعه صادرات غیرنفتی برای عبور از آسیب‌پذیری اقتصاد وابسته به نفت و دستیابی به رشد پایدار، اولویتی راهبردی برای ایران است. در این میان، صنایع تبدیلی غذایی به‌عنوان پیونددهنده زنجیره ارزش کشاورزی با بازارهای منطقه‌ای، از مزیت جغرافیایی و توان اشتغال‌زایی بالایی برخوردار است؛ اما این بخش هنوز نتوانسته به پتانسیل واقعی صادراتی خود دست یابد. این مقاله با طراحی چارچوبی مبتنی بر هوش مصنوعی، داده‌های تاریخی (۲۰۰۰ تا ۲۰۲۲) را با ادراکات ۱۵۰ خبره صنعتی تلفیق کرده تا مسیرهای تحول این صنعت را تبیین کند. یافته‌های حاصل از مدل‌های یادگیری ماشین با تبیین‌پذیری مدل SHAP نشان می‌دهد که متغیرهای «ظرفیت فرآوری مواد غذایی»، «بهره‌وری صنعتی» و «خلق ارزش در بخش کشاورزی»، بیشترین سهم را در ارتقای عملکرد صادراتی دارند؛ درحالی‌که نرخ ارز نقشی مهم اما با رتبه اثربخشی پایین‌تر ایفا می‌کند. در نقطه مقابل، تحلیل خوشه‌بندی خبره‌محور گلوگاه‌های اصلی در عدم تحقق این پتانسیل شامل «ناپایداری نرخ ارز»، «نااطمینانی در سیاست‌گذاری‌های دولتی» و «ضعف در بازاریابی و قابلیت‌های ورود به بازارهای بین‌المللی» را ریشه‌دار در موانع نهادی و استراتژیک می‌داند. از منظر اقتصاد صنعتی، پیام کلیدی مقاله این است که جهش صادراتی پایدار، بدون رفع نااطمینانی‌های سیاستی، ارتقای بهره‌وری زنجیره تأمین و توانمندسازی تجاری بنگاه‌ها، صرفاً با تکیه بر ابزار تعدیل نرخ ارز حاصل نخواهد شد.

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1.Introduction

International trade has long been recognized as a key driver of economic development by generating foreign exchange, facilitating technology transfer, enhancing productivity, and expanding production capacity (Krugman et al., 2018). However, excessive reliance on a limited range of export commodities exposes economies to external shocks and constrains long-term industrial competitiveness (Hausmann et al., 2007). Similar to many resource-dependent economies, Iran has historically relied heavily on oil revenues, making export diversification a strategic national priority. Accordingly, Iran's Seventh National Development Plan targets an annual 23% growth in non-oil exports to strengthen economic resilience and reduce dependence on petroleum revenues (Islamic Republic of Iran, 2023).

Within this strategy, agriculture and agro-based industries play a pivotal role because of their strong linkages with domestic production, employment, food security, and export diversification (Anderson, 2016; Abnar et al., 2020). Nevertheless, sustainable competitiveness increasingly depends on moving beyond raw agricultural exports toward higher value-added products through processing, branding, quality improvement, and integration into global value chains (Kaplinsky & Morris, 2001; Gereffi et al., 2005). Food manufacturing industries are therefore critical, as they transform agricultural raw materials into value-added products, reduce post-harvest losses, stabilize seasonal supply, create employment, and improve access to international markets (Wilkinson & Rocha, 2013; FAO, 2022). Compared with many capital-intensive industries, food manufacturing requires relatively moderate investment while offering substantial opportunities for industrial upgrading and export diversification (Torkamani & Zoghipour, 2008).

The strategic importance of this sector is evident in Iran's recent trade performance. Agricultural exports reached approximately USD 8.46 billion, accounting for 13.5% of total non-oil exports valued at USD 62.59 billion (IRICA, 2021). Processed food products, including dairy products, tomato paste, confectionery, and other processed agricultural goods, constitute a significant share of these exports. At the same time, considerable untapped opportunities remain in neighboring markets. Countries such as Saudi Arabia, the United Arab Emirates, Oman, Kuwait, and Qatar annually import billions of dollars of dairy products, while global imports of tomato paste exceed USD 4.5 billion, compared with Iran's exports of only USD 126 million (ITC, 2023). These figures highlight the substantial gap between Iran's existing export performance and its regional and global market potential.

Despite these advantages, Iran's food industry has not fully realized its international competitiveness. Previous studies have identified exchange rate instability, production inefficiencies, technological limitations, weak branding, inadequate marketing, quality-related issues, logistics constraints, and limited participation in global value chains as the principal barriers to export development (Sedaghat, 2007; Torkamani & Zoghipour, 2008; Nejatianpour & Esmaeili, 2016; Mousavi Khaledi et al., 2020). Most existing research has relied on conventional econometric approaches, particularly gravity models and panel-data techniques, to explain export performance through variables such as exchange rates, market size, trade costs, and economic distance (Wardani et al., 2018; Szekelyhidi, 2018; Bekele & Mersha, 2019). Although these studies have significantly advanced the understanding of trade determinants, many empirical applications rely on relatively predefined functional specifications and a limited set of theoretically selected relationships. Econometric approaches are not inherently restricted to linear relationships and can accommodate nonlinearities, interaction effects, structural breaks, and regime-dependent dynamics through appropriate model specifications. However, when the objective is exploratory prediction in the presence of multiple potentially interacting economic, technological, institutional, and structural variables, machine-learning methods can provide a complementary data-driven approach for identifying complex predictive patterns without requiring all functional relationships and interactions to be specified ex ante.

Addressing these complexities requires moving beyond the traditional objective of identifying export determinants toward designing Industrial Transformation Pathways, defined as strategic trajectories through which industries evolve toward more competitive, technologically advanced, sustainable, and globally integrated production systems (Dosi, 1982; Freeman & Perez, 1988; Perez, 2010; OECD, 2021). Such pathways emphasize the dynamic interaction among technological capabilities, innovation, organizational development, market positioning, institutional quality, and resource efficiency rather than production expansion alone. For emerging economies such as Iran, where industrial development is simultaneously influenced by macroeconomic instability, investment constraints, technological gaps, energy intensity, trade restrictions, and changing global market requirements, capturing all potentially nonlinear and interacting relationships through a single predefined empirical specification can be challenging. Data-driven machine-learning approaches can therefore complement conventional econometric analysis by exploring complex predictive patterns and interactions among multiple variables.

Recent advances in artificial intelligence (AI) and machine learning (ML) offer valuable tools for analyzing multidimensional and complex systems. Modern and widely used machine-learning algorithms, such as Random Forest and Extreme Gradient Boosting (XGBoost), are particularly well suited to capturing nonlinear relationships and complex interactions among variables (Breiman, 2001; Chen & Guestrin, 2016). Unlike some conventional econometric specifications that rely on predefined functional forms, these algorithms can flexibly model complex patterns in the data, making them useful complementary approaches for predictive analysis in multidimensional economic and industrial systems.Moreover, the emergence of Explainable Artificial Intelligence (XAI), particularly the SHAP framework, enables researchers to interpret AI models by quantifying the contribution of individual variables to prediction outcomes (Lundberg & Lee, 2017; Lundberg et al., 2020). Consequently, AI can move beyond prediction toward strategic knowledge discovery by identifying key transformation drivers, prioritizing industrial capabilities, and supporting evidence-based policymaking (Wuest et al., 2016; Kusiak, 2018; Tao et al., 2019). Nevertheless, applications of explainable AI for identifying industrial transformation pathways in agro-based industries, particularly in developing countries, remain scarce.

Accordingly, this study addresses a broader strategic question than previous export studies: Which economic, technological, structural, and managerial capabilities should be prioritized to transform Iran's food manufacturing industry into a competitive, technology-oriented, and globally integrated sector? To answer this question, the study proposes an integrated AI-based framework combining longitudinal time-series data with expert knowledge collected from industry stakeholders. Machine learning models identify and rank the dynamic drivers of export competitiveness, while expert-based analysis validates these findings and translates them into practical industrial transformation pathways. Unlike previous studies that primarily diagnose export determinants using conventional econometric techniques, this research integrates explainable artificial intelligence with industrial expertise to develop an evidence-based roadmap for transforming Iran's food manufacturing sector into a competitive, value-added, and globally connected industry.

2. Literature Review

2.1. Export Competitiveness in Food Manufacturing

Export competitiveness has long been recognized as a fundamental determinant of industrial development and economic diversification. Previous studies have primarily explained agricultural and food exports using macroeconomic variables, including exchange rates, income, production capacity, market size, and trade costs. International studies employing gravity models (Bekele & Mersha, 2019; Braha et al., 2017; Ebaidalla & Awad, 2015; Mosikari & Eita, 2016; Natale et al., 2015; Szekelyhidi, 2018; Wardani et al., 2018) consistently demonstrate that market size, economic distance, and exchange rate movements significantly influence export performance. Similar evidence has been reported for Iran, where gravity-based analyses identified exchange rates, GDP, sanctions, and production capacity as important determinants of agricultural and food exports (Abnar et al., 2020; Akbari et al., 2017; Harati et al., 2015; Khadiv & Asgari, 2020; Koochakzadeh & Karbasi, 2015; Shafiei & Aghapour Sabbaghi, 2016; Souri, 2017; Zarif et al., 2011; Ziyaee Bigdeli et al., 2013). Although these studies substantially improved the understanding of export determinants, they predominantly focused on explaining historical trade patterns rather than identifying future industrial development trajectories.

2.2. Industrial Transformation and Strategic Development

In this study, an industrial transformation pathway refers to a structured strategic trajectory through which a food manufacturing industry develops its productive, technological, organizational, market, and institutional capabilities to achieve sustained improvements in competitiveness and international market integration. Thus, the term refers not to a single intervention, but to a coherent configuration of capabilities and strategic priorities that can guide the sector's transition toward higher-value and more competitive production.

Recent industrial policy literature emphasizes that long-term competitiveness depends not only on production growth but also on industrial transformation through technological upgrading, productivity improvement, innovation, institutional quality, and value-chain integration (Dosi, 1982; Freeman & Perez, 1988; OECD, 2021; Perez, 2010). Accordingly, transformation pathways describe dynamic sequences of structural changes that enable industries to achieve sustainable competitiveness under changing economic and technological conditions. In agro-food industries, these pathways involve strengthening productivity, increasing value addition, improving quality standards, expanding market capabilities, and enhancing technological readiness rather than relying solely on traditional comparative advantages.

2.3. Artificial Intelligence in Industrial Decision-Making

The rapid development of artificial intelligence has expanded the analytical tools available for industrial research by facilitating the exploration of complex nonlinear relationships and interactions among multiple variables. Although econometric methods can accommodate such complexities through appropriate nonlinear, interaction-based, structural-break, or regime-dependent specifications, machine-learning approaches provide a flexible complementary framework when the underlying functional relationships are not known in advance or when multiple interactions may be relevant. Machine learning algorithms, particularly Random Forest (Breiman, 2001) and Extreme Gradient Boosting (Chen & Guestrin, 2016), have demonstrated high predictive performance in economic forecasting, industrial performance evaluation, and supply-chain analysis (Kusiak, 2018; Wuest et al., 2016). More recently, Explainable Artificial Intelligence (XAI) has addressed the interpretability challenge of machine learning models. The SHAP framework enables decomposition of model predictions into variable-specific contributions, thereby supporting transparent policy interpretation and evidence-based decision-making (Lundberg & Lee, 2017; Lundberg et al., 2020). Consequently, AI has evolved from a prediction tool into a strategic instrument for industrial policy analysis.

2.4. AI Applications in Industrial Transformation Studies

The application of AI has increasingly extended beyond forecasting toward supporting industrial transformation and strategic planning. Recent studies have employed machine learning to identify technological transition patterns, evaluate industrial resilience, optimize production systems, and prioritize development strategies in manufacturing and supply chains (Baryannis et al., 2019; Ivanov & Dolgui, 2020; Kusiak, 2018; Tao et al., 2019; Wuest et al., 2016). However, these applications remain concentrated in advanced manufacturing economies. In the food industry, particularly within developing countries, AI has been used mainly for prediction, demand forecasting, quality assessment, and process optimization, while studies integrating explainable AI with expert knowledge to formulate industrial transformation pathways remain extremely limited.

2.5. Research Gap and Contribution

Overall, existing literature has provided valuable insights into the determinants of agricultural and food exports, the challenges of export development, and the potential of artificial intelligence for industrial analysis. Nevertheless, three major gaps remain. First, previous studies have largely emphasized explaining export performance rather than identifying strategic transformation pathways. Second, while econometric approaches can explicitly model nonlinearities and interactions through appropriate specifications, empirical applications in this literature have often focused on a relatively limited set of predefined relationships among macroeconomic and trade variables. Machine-learning methods can complement these approaches by exploring broader predictive patterns and potentially complex interactions among macroeconomic, industrial, technological, and institutional factors. Third, few studies integrate longitudinal economic evidence with expert knowledge through explainable artificial intelligence to support industrial policymaking. Addressing these gaps, the present study proposes an integrated AI-based framework combining machine learning, SHAP explainability, and expert-based Self-Organizing Maps (SOM) to identify the critical capabilities and policy priorities required for transforming Iran's food manufacturing industry into a competitive, technology-oriented, and globally integrated sector. Unlike previous research, this framework moves beyond identifying what determines exports toward explaining how industrial transformation can be strategically achieved, thereby providing an evidence-based foundation for industrial policy and long-term sectoral development.

3. Materials and Methods

3.1. Research Design and Analytical Framework

This study develops an integrated artificial intelligence-based framework to assess industrial transformation pathways in Iran's food manufacturing sector. Unlike conventional studies that mainly focus on identifying determinants of export performance through econometric approaches, this research aims to move beyond factor identification and provide a strategic understanding of how industrial capabilities can be transformed toward a more competitive and globally integrated food manufacturing system.

The methodological framework consists of two complementary analytical stages. In the first stage, artificial intelligence-based time-series models are applied to identify the dynamic drivers of food industry export performance in Iran. This stage captures historical relationships between export performance and a set of macroeconomic, industrial, technological, and institutional factors over the period 2000–2022. Since industrial competitiveness is characterized by complex interactions, nonlinear relationships, and possible threshold effects, machine learning algorithms are employed instead of relying solely on traditional linear specifications.

In the second stage, an expert-based artificial intelligence clustering framework is developed to identify feasible transformation pathways. Although historical data provide evidence regarding the factors associated with export performance, they cannot fully capture managerial knowledge, institutional constraints, and practical implementation challenges. Therefore, expert knowledge from industrial managers, policymakers, exporters, and sectoral organizations is incorporated through an AI-based clustering approach.

The combination of these two analytical perspectives allows the study to answer two complementary questions:

1. Which factors have historically influenced the export competitiveness of Iran's food industry?
2. Which transformation pathways should be prioritized to enhance future industrial competitiveness?

Accordingly, the proposed framework combines historical evidence from machine learning models with forward-looking strategic insights derived from industrial stakeholders.

3.2. Data Sources and Variable Selection

The quantitative component of this study is based on annual time-series data covering the period 2000–2022, a timeframe selected to ensure the availability, consistency, and comparability of macroeconomic, industrial, and trade statistics. Data were compiled from several authoritative national and international sources, including the Central Bank of Iran (CBI), Statistical Center of Iran (SCI), Ministry of Industry, Mine and Trade (MIMT), Islamic Republic of Iran Customs Administration (IRICA), the World Bank, and the International Trade Centre (ITC). Following international trade theory and the industrial competitiveness literature, the annual export value of Iran's food manufacturing industry was selected as the dependent variable because export performance provides a comprehensive measure of industrial competitiveness, reflecting not only production capacity but also technological capability, product quality, international market access, and participation in global value chains. For developing economies, food manufacturing exports are particularly important because they generate substantially higher value added than exports of raw agricultural commodities, reduce post-harvest losses, create employment opportunities, and strengthen foreign exchange earnings (Torkamani & Zoghipour, 2008). Consistent with previous studies, export performance is therefore considered an appropriate proxy for assessing the competitive position and structural development of Iran's food manufacturing sector (Wardani et al., 2018; Abnar et al., 2020).

The explanatory variables were selected to capture the macroeconomic, industrial, technological, financial, and institutional dimensions influencing export competitiveness. Macroeconomic conditions were represented by the inflation rate, exchange rate, gross domestic product (GDP), gross fixed capital formation, interest rate and. Inflation reflects macroeconomic instability and rising production costs, whereas the exchange rate affects international price competitiveness while excessive volatility may discourage investment and increase production uncertainty (Abnar et al., 2020; Kohansal & Mahmoudi, 2020; Mousavi Khaledi et al., 2020). The exchange-rate variable is measured in nominal terms. A nominal exchange rate was retained to capture the observed domestic-currency price of foreign currency and its associated macroeconomic and cost effects during the study period. Because inflation is included separately as an explanatory variable, the model allows the predictive contribution of exchange-rate movements to be evaluated alongside domestic price instability rather than treating nominal depreciation as a direct measure of changes in relative international prices. Accordingly, the exchange-rate variable should not be interpreted as a direct measure of real price competitiveness. The exchange-rate variable is measured as the nominal exchange rate of the Iranian rial against the US dollar (IRR/USD), expressed as Iranian rials per US dollar. GDP and gross fixed capital formation represent the overall scale of economic activity, production infrastructure, and investment capacity that support industrial upgrading and export expansion, while the interest rate captures financing costs and firms' ability to invest in technology and production (Anderson, 2016; Tinbergen, 1962). Industrial and technological capabilities were represented by food machinery imports, agricultural value added, food manufacturing output, and food industry productivity. Imports of food-processing machinery serve as a proxy for technology acquisition and industrial modernization, agricultural value added reflects the availability and quality of domestic raw materials, food manufacturing output measures industrial production capacity, and productivity represents the efficiency with which resources are transformed into internationally competitive products, which Porter (1990) identifies as the fundamental source of sustainable competitiveness. Finally, an economic sanctions dummy variable was incorporated to capture major structural shocks affecting Iran's industrial and trade environment. The variable was coded as 0 for 2000–2009, 1 for 2010–2015, 0 for 2016–2018, and 1 for 2019–2022, representing periods of intensified international sanctions that substantially affected financial transactions, technology transfer, industrial investment, and international trade. Similar structural shock variables have been widely employed in empirical studies examining the impact of sanctions on Iran's trade performance and export competitiveness (Ziyaee Bigdeli et al., 2013). Collectively, these variables provide a comprehensive representation of the economic, industrial, technological, and institutional factors shaping the export performance of Iran's food manufacturing industry.

3.3. Artificial Intelligence-Based Time-Series Modeling

To identify nonlinear relationships between food industry exports and explanatory variables, two machine learning algorithms are applied: Random Forest (RF) and Extreme Gradient Boosting (XGBoost).

Machine-learning approaches are increasingly used in economic and industrial studies because they provide flexible tools for capturing complex predictive patterns and interactions among variables without requiring the researcher to specify all functional forms and interaction structures in advance.

3.3.1. Random Forest Model

The first machine learning algorithm employed in this study is the Random Forest (RF) model, introduced by Breiman (2001). Random Forest belongs to the family of ensemble learning methods and constructs a large number of independent decision trees using randomly selected subsets of observations and explanatory variables. The final prediction is obtained by aggregating the results of individual trees, which improves predictive stability and reduces the risk of overfitting.

The application of Random Forest is particularly relevant for industrial competitiveness analysis because the determinants of export performance are rarely independent or linearly related. For instance, the effect of technological upgrading on food industry exports may depend on investment capacity, exchange rate conditions, availability of agricultural inputs, and macroeconomic stability. Econometric regression models can represent nonlinearities and interaction effects when these relationships are specified appropriately. However, such specifications generally require the researcher to define the relevant functional forms and interactions ex ante. Random Forest provides a complementary data-driven approach that can flexibly explore complex nonlinear patterns and interactions directly from the observed data.

Another important advantage of Random Forest is its ability to estimate the relative importance of explanatory variables. In this research, the model is not used merely as a forecasting tool; rather, it serves as an exploratory mechanism to identify which economic and industrial factors have the strongest association with export competitiveness. This characteristic is particularly valuable in the context of industrial transformation studies, where the objective is not only prediction but also identifying strategic intervention areas.

Following Breiman (2001), the Random Forest model can be represented as an ensemble of multiple decision trees:

$$\hat{Y} = \frac{1}{B}\sum_{b=1}^{B} T_b\,(X) \tag{1}$$

where $T_b\,(X)$ represents the prediction generated by the b-th decision tree and B represents the total number of trees. Increasing the number of trees generally improves prediction robustness while maintaining model stability.

3.3.2. Extreme Gradient Boosting (XGBoost) Model

The second artificial intelligence approach applied in this study is Extreme Gradient Boosting (XGBoost), developed by Chen and Guestrin (2016). XGBoost is an advanced implementation of gradient boosting algorithms designed to improve predictive performance through sequential learning. Unlike Random Forest, where trees are independently constructed and subsequently combined, XGBoost develops trees sequentially, with each new tree attempting to correct the prediction errors of previous models.

The methodological advantage of XGBoost is its capability to capture complex nonlinear relationships while incorporating regularization mechanisms that reduce model complexity and prevent overfitting. These characteristics have resulted in widespread application of XGBoost in economic forecasting, financial modelling, industrial analytics, and decision-support systems.

In the context of Iran's food industry, export competitiveness is influenced by simultaneous interactions among production capacity, technology acquisition, macroeconomic conditions, and external constraints. XGBoost is therefore appropriate because it can identify hidden relationships that may not be observable through conventional analytical approaches.

The general objective function of XGBoost can be expressed as:

$$Obj = \sum_{i} l(y_i, \hat{y}_i) + \sum_{k} \Omega(f_k) \tag{2}$$

where the first component represents the prediction error and the second component controls model complexity through regularization (Chen & Guestrin, 2016).

The combination of Random Forest and XGBoost provides methodological robustness because both models are based on tree-learning structures but approach nonlinear modelling from different perspectives. If both algorithms identify similar influential factors, confidence in the identified transformation drivers increases.

3.3.3. Model Training, Validation, and Accuracy Evaluation

Since the objective of this study is to analyze industrial dynamics over time, special attention is given to preserving the temporal structure of the dataset. Unlike conventional machine learning applications where random sampling is commonly applied, random splitting of time-series observations may generate information leakage because future information can unintentionally influence model training. Therefore, an expanding-window time-series cross-validation procedure was employed to preserve the temporal structure of the dataset. The model was initially trained on observations from 2000–2015 and used to predict 2016; the training window was then expanded by one year and the procedure repeated sequentially through 2022. Model performance was evaluated across the resulting out-of-sample predictions using MAPE rather than relying on a single train–test split. The performance of competing AI models is assessed using the Mean Absolute Percentage Error (MAPE). MAPE is selected because it provides an intuitive measure of prediction accuracy by expressing prediction errors as percentages, allowing direct comparison between models.The MAPE is calculated as:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (3)$$

where represents the observed export value and represents the predicted value. The model with the lowest MAPE value is considered the most accurate predictive framework and is subsequently selected for explainability analysis. where (yi) represents the observed export value and (^yi) represents the predicted value.

The model with the lowest MAPE value is considered the most accurate predictive framework and is subsequently selected for explainability analysis.

3.4. Explainable Artificial Intelligence Analysis

Although machine learning models provide strong predictive capabilities, their complex structures often create interpretation challenges, commonly referred to as the "black-box" problem. In policy-oriented research, predictive accuracy alone is insufficient because decision-makers need to understand why a model produces a particular outcome and which factors should be targeted through interventions. Therefore, this study incorporates Explainable Artificial Intelligence (XAI) using the SHAP (SHapley Additive exPlanations) framework proposed by Lundberg and Lee (2017).

In this research, SHAP analysis serves three main interpretive purposes. First, it identifies the variables that provide the largest contributions to the model's predictions of Iran's food industry export performance. For example, the analysis can indicate whether variables related to technological upgrading, productivity, exchange-rate conditions, or investment capacity contain relatively greater predictive information within the fitted model.

Second, SHAP values help interpret the direction and pattern of variable contributions to individual model predictions. A variable may have high predictive importance without exhibiting a uniformly positive or negative contribution across all observations. For example, machinery imports may be associated with higher predicted export performance under some observed conditions while contributing less strongly under others, reflecting possible interactions and nonlinearities captured by the model.

Third, SHAP analysis provides an interpretable basis for connecting predictive patterns identified by the machine-learning model with industrial policy discussion. These results should not be interpreted as establishing causal effects or identifying policy interventions with guaranteed impacts. Rather, they highlight patterns and variables that warrant further economic interpretation and policy attention.

Thus, XAI represents a critical methodological component of this study because it makes the predictive structure of the artificial intelligence model more transparent and facilitates the interpretation of model-based evidence within a broader industrial policy framework.

3.5. Expert-Based AI Clustering Framework for Transformation Pathway Identification

Historical data analysis provides valuable evidence regarding the factors associated with export competitiveness; however, industrial transformation is a forward-looking process involving strategic choices, organizational capabilities, and institutional constraints that cannot be fully captured through quantitative indicators alone.

Therefore, this study incorporates expert knowledge through an AI-based clustering framework. The purpose of this stage is not to replace empirical modelling but to complement it by integrating the tacit knowledge of industrial stakeholders into the pathway identification process.

A structured questionnaire was developed based on two sources: (1) variables and predictive patterns identified as influential within the AI time-series models and SHAP analysis, and (2) the broader literature on industrial transformation, Industry 4.0 adoption, competitiveness, and global value chain integration. The questionnaire evaluated the perceived importance and readiness of different transformation dimensions, including:

1. technological upgrading and Industry adoption;
2. production efficiency and productivity improvement;
3. export capability development;
4. international standards and quality management;
5. supply chain resilience;
6. innovation capacity;
7. branding and international marketing;
8. institutional and financial barriers.

The survey was conducted among 150 experts and industrial stakeholders selected from different components of Iran's food manufacturing ecosystem. Participants included food industry managers, exporters, representatives of industrial associations, experts introduced through the Iran Chamber of Commerce, governmental organizations related to industry and agriculture, and relevant professional organizations. The objective of collecting expert opinions was not to obtain simple rankings of factors but to identify underlying strategic patterns among stakeholders with different perspectives and experiences.

3.5.1. Self-Organizing Map (SOM) Approach

To analyze expert responses, this study applies the Self-Organizing Map (SOM) algorithm developed by Kohonen (1990). SOM is an unsupervised artificial neural network technique designed to identify hidden structures and patterns within multidimensional datasets. Unlike supervised machine learning methods that require predefined classes, SOM discovers natural groupings based on similarities among observations. This characteristic makes it suitable for transformation pathway analysis, where the objective is to uncover alternative strategic configurations rather than classify observations according to predetermined categories.

In this study, each expert represents an observation characterized by their evaluation of transformation dimensions. The SOM algorithm maps experts with similar strategic perceptions into the same cluster, allowing the identification of distinct perspectives regarding the future direction of Iran's food industry. The resulting clusters are interpreted as alternative transformation pathways. For example, one cluster may emphasize technology-intensive transformation through automation and digitalization, while another may prioritize export market expansion, branding, and global value chain integration. A third cluster may reflect a resilience-oriented pathway emphasizing domestic capability development and supply chain security. The advantage of SOM is that it enables the identification of complex strategic patterns that may remain hidden when using traditional statistical ranking methods.

3.6. Integration of AI Outputs for Developing Industrial Transformation Pathways

The final analytical stage integrates the outputs of machine learning models, explainable artificial intelligence analysis, and expert-based clustering to develop an evidence-based framework for identifying industrial transformation pathways in Iran's food manufacturing sector. The time-series machine learning models provide empirical insights into the historical dynamics of export competitiveness by capturing the complex and nonlinear relationships between industrial, technological, macroeconomic, and external factors. Subsequently, the SHAP-based explainability analysis reveals the relative contribution and direction of influence of each determinant, transforming the predictive outcomes of artificial intelligence models into interpretable strategic insights. In parallel, the expert-based SOM clustering approach incorporates the tacit knowledge and practical perspectives of industrial stakeholders to identify feasible transformation trajectories under existing institutional and market conditions. Accordingly, the three stages serve complementary rather than independent validation roles: ML identifies predictive patterns, SHAP interprets their contribution, and expert-based SOM translates these empirical insights into distinct strategic configurations. The resulting configurations are interpreted as transformation pathways based on their dominant combinations of capabilities and priorities.

By integrating these three analytical layers, this study establishes a comprehensive transformation pathway framework that combines historical evidence, model-based interpretation, and industry-specific strategic knowledge. This integrated approach addresses an important limitation in previous export competitiveness studies, which have predominantly concentrated on identifying statistical determinants of trade performance while providing limited guidance on how industries can strategically transform toward higher levels of competitiveness. Therefore, the proposed framework extends beyond explaining export performance and provides a systematic approach for identifying the technological capabilities, industrial priorities, and policy interventions required to transform Iran's food industry into a more competitive, technology-oriented, and globally integrated manufacturing sector.

Given the limited sample size, model stability was assessed through repeated resampling and sensitivity analysis. The feature-importance rankings remained broadly consistent across validation runs, indicating that the main findings were not driven by a small number of individual observations.

4. Results

4.1. Machine Learning Model Performance and Key Predictive Factors of Export Performance

The first analytical stage aimed to identify the main variables contributing to the predictive representation of export performance in Iran's food manufacturing industry using machine-learning-based approaches. The objective of this stage is to examine patterns of association and predictive contribution within the observed data rather than to establish causal relationships among the explanatory variables and export performance.

Two ensemble learning algorithms, namely Random Forest (RF) and Extreme Gradient Boosting (XGBoost), were employed to model the relationship between food industry exports and explanatory variables during 2000–2022. The models were evaluated using the Mean Absolute Percentage Error (MAPE) criterion. The results indicate that both models were able to capture the general pattern of export dynamics; however, XGBoost achieved superior predictive performance compared with Random Forest.

Table 1. Performance comparison of machine learning models

Model	Training MAPE	Testing MAPE	Performance ranking
Random Forest	8.9%	13.4%	Second
XGBoost	6.3%	10.1%	First

Source: Research Finding

The lower prediction error obtained by XGBoost confirms its stronger capability in representing the complex nonlinear structure of food export dynamics. Therefore, XGBoost was selected as the final predictive model for the subsequent explainable artificial intelligence analysis.

The relatively low prediction error of the selected model suggests that export competitiveness in Iran's food manufacturing sector is not adequately represented by a single explanatory factor. Instead, the model captures export performance through the combined contribution of variables related to industrial capabilities, value creation, productivity conditions, market competitiveness, and macroeconomic conditions.

This finding is particularly important in the context of Iran, where export performance is often interpreted mainly through exchange rate movements or external constraints. The machine learning results suggest that, although macroeconomic variables contribute to the prediction of export outcomes, variables associated with internal industrial capabilities provide a larger share of the predictive information captured by the model.

The gain-based feature importance analysis of the XGBoost model indicates that variables related to production capacity, industrial value creation, and productivity provide the largest contributions to the predictive structure of the model.

Table 2. Relative importance of explanatory variables based on XGBoost gain

Rank	Variable	Relative importance (%)	Economic interpretation
1	Food manufacturing output value	24.1	Represents industrial scale and production capacity
2	Food industry productivity	19.8	Determines production efficiency and cost competitiveness
3	Agricultural value added	15.6	Reflects the strength of upstream supply chains
4	Exchange rate	11.7	Captures changes in relative prices and export competitiveness
5	Gross fixed capital formation	9.8	Indicates long-term expansion of productive capacity
6	Machinery imports	7.8	Supports technological upgrading and process improvement
7	Inflation rate	5.9	Represents macroeconomic instability and cost uncertainty
8	Interest rate	3.4	Affects access to financial resources and investment conditions
9	Sanctions intensity	1.9	Represents external constraints with relatively lower direct predictive contribution

Source: Research Finding

The prominence of food manufacturing output value indicates that this variable provides the largest gain contribution to the predictive structure of the XGBoost model. This result highlights the importance of industrial scale and production capacity in explaining variation in food export performance. In substantive terms, industries that successfully participate in international markets require not only access to agricultural resources but also the capacity to transform these resources into standardized, high-quality, and internationally competitive products.

Food industry productivity represents the second-largest source of gain in the model. Its high importance indicates that differences in production efficiency provide substantial predictive information regarding export performance within the fitted model. This pattern is consistent with the economic mechanisms through which higher productivity may support export competitiveness, including lower unit costs, improved resource utilization, reduced production losses, and a greater capacity to meet quality and market requirements. However, the machine-learning results do not independently establish these mechanisms as causal effects.

Similarly, the high gain contribution of agricultural value added emphasizes the importance of the relationship between agricultural production and downstream food manufacturing. A competitive food industry depends not only on processing capacity but also on the availability, quality, and economic performance of upstream agricultural supply chains. Export development should therefore be considered within an integrated agricultural–industrial value chain rather than as an isolated manufacturing activity.

Machinery imports provide a moderate contribution to the predictive structure of the model. This result suggests that technological upgrading and modern production equipment contain relevant information for explaining export performance, although their contribution is smaller than that of production capacity and productivity-related variables. Technology acquisition alone is therefore unlikely to represent a sufficient condition for export competitiveness; its effectiveness depends on complementary factors such as productivity management, organizational capabilities, market access, and the effective utilization of installed production capacity.

The exchange rate also makes a substantial gain contribution to the model. However, the gain measure does not indicate whether the effect of exchange rate movements on exports is positive, negative, or nonlinear. These patterns are examined separately in the subsequent SHAP analysis. The importance of the exchange rate nevertheless indicates that changes in relative prices and broader macroeconomic conditions provide relevant predictive information for the model.

Sanctions intensity has the lowest predictive contribution among the variables included in the fitted model. Conditional on the other variables considered, this result indicates that the sanctions variable provides less incremental predictive information for the model's export predictions than the principal production-, productivity-, and value-creation-related variables.

This finding should not be interpreted as evidence that sanctions have a limited economic or causal effect on Iran's food industry. Sanctions may influence export performance indirectly through multiple channels, including financial transactions, access to imported technology and intermediate inputs, exchange-rate instability, investment conditions, transportation costs, and broader macroeconomic uncertainty. Some of these channels may also be represented by other variables included in the model. Consequently, the relatively low predictive contribution of the sanctions variable should be interpreted only as a characteristic of the fitted predictive model and the selected set of variables, rather than as a measure of the overall economic impact of sanctions.

4.2. Explainable AI Analysis Using SHAP: Understanding the Direction and Economic Meaning of Export Drivers

Although machine learning models can provide strong predictive performance, the internal structure through which explanatory variables contribute to individual predictions is often difficult to interpret. In the context of industrial policy and transformation strategy, identifying variables with high predictive importance alone is insufficient; policymakers also need to understand how individual variables contribute to model predictions and whether these contributions are predominantly positive, negative, or nonlinear. Therefore, the present study applies the SHAP (Shapley Additive Explanations) approach to interpret the output of the selected XGBoost model.

The SHAP analysis complements, rather than replicates, the gain-based feature importance analysis presented in Table 2. XGBoost gain measures the contribution of a variable to improvements in the model's tree-based objective function during the construction of decision trees. SHAP analysis, in contrast, decomposes individual model predictions into variable-specific marginal contributions. The two approaches therefore provide different measures of model importance and should not be interpreted as interchangeable.

For each explanatory variable, the mean absolute SHAP value measures the average magnitude of its contribution to model predictions across all observations. For comparability across variables, these values were normalized by dividing each variable's mean absolute SHAP value by the sum of the mean absolute SHAP values across all explanatory variables. The resulting normalized values are reported in Table 3 as relative SHAP importance. Accordingly, the values in Table 3 sum to one by construction and should not be interpreted as raw mean absolute SHAP values.

Because the absolute magnitude of SHAP values does not indicate whether a variable increases or decreases the predicted outcome, the direction and pattern of each relationship were examined separately using signed SHAP values. The classification of effects reported in Table 3 is therefore based on the signed SHAP results and their distribution across observations rather than on the normalized absolute SHAP importance values.

The SHAP analysis broadly supports the main pattern identified by the gain-based feature importance analysis while providing a distinct interpretation of the fitted model. Variables associated with industrial capacity, productivity, and value creation account for the largest average contributions to model predictions, whereas the signed SHAP analysis provides additional evidence regarding the direction and potential nonlinear pattern of these contributions.

Table 3. Ranking and interpretation of export competitiveness drivers based on SHAP values

Rank	Variable	Normalized mean absolute SHAP importance	Direction from signed SHAP analysis	Strategic interpretation
1	Food manufacturing output value	0.228	Positive	Expansion of industrial capacity and production scale
2	Food industry productivity	0.206	Positive	Reduction of production costs and improvement of competitiveness
3	Agricultural value added	0.147	Positive	Strengthening raw material supply and value chains
4	Exchange rate	0.129	Nonlinear	Short-term competitiveness gains but uncertainty effects
5	Gross fixed capital formation	0.102	Positive	Long-term industrial capacity development
6	Machinery imports	0.074	Positive but conditional	Technology improvement depending on absorption capacity
7	Inflation rate	0.061	Negative	Higher uncertainty and production costs
8	Interest rate	0.036	Negative	Higher financing constraints
9	Sanctions intensity	0.017	Limited negative effect	External constraint with lower direct impact

Source: Research Finding, Note: Normalized SHAP importance is calculated by dividing each variable's mean absolute SHAP value by the sum of mean absolute SHAP values across all explanatory variables. Therefore, the reported values sum to 1 by construction. The direction of effects is assessed separately using signed SHAP values.

The prominence of food manufacturing output value in the SHAP ranking indicates that this variable makes the largest average contribution to the model's predictions of export performance. From an economic perspective, this pattern is consistent with the argument that export competitiveness is closely associated with the productive scale and capacity of the domestic food industry.

A higher production scale allows firms to benefit from economies of scale, reduce unit costs, maintain stable supply for foreign customers, and comply with international market requirements. Therefore, increasing the capacity and efficiency of food processing industries represents a central pathway for improving Iran's position in regional and global food markets.

The second most influential factor is productivity. The strong contribution of productivity confirms that the competitiveness challenge of Iran's food industry is not merely a production volume issue but largely a productivity issue. In international markets, particularly in neighboring countries with increasing competition from Turkey, Saudi Arabia, and other regional producers, firms need to compete through efficiency, quality consistency, and supply reliability rather than relying only on lower prices.

The SHAP results also highlight the important role of agricultural value added. This finding supports the argument that food manufacturing transformation should be approached through an integrated agriculture–industry value chain perspective. Iran possesses considerable agricultural potential; however, the economic benefits of this potential depend on the ability to transform agricultural outputs into processed products with higher value added.

Table 4. Economic interpretation of major SHAP-based findings

Variable	SHAP interpretation	Implication for industrial transformation
Food manufacturing output value	Higher industrial output increases export potential	Promote scalable and export-oriented production
Productivity	Efficiency improvements strongly enhance competitiveness	Focus on process optimization and waste reduction
Agricultural value added	Strong agricultural-industrial linkage supports exports	Develop integrated value chains
Exchange rate	Effect depends on production conditions	Avoid excessive reliance on currency depreciation
Machinery imports	Benefits depend on managerial and technical capability	Improve technology absorption capacity
Inflation	Creates uncertainty and reduces competitiveness	Strengthen macroeconomic stability
Interest rate	Limits investment capacity	Improve industrial financing mechanisms
Sanctions	Lower direct contribution than internal factors	Focus on domestic capability building

Source: Research Finding

Exchange Rate Effects: Beyond the Traditional Export Incentive Mechanism

One of the most important findings of the SHAP analysis concerns the role of the exchange rate. Conventional trade theory suggests that currency depreciation can improve export price competitiveness when it lowers the relative price of domestic goods compared with foreign goods. However, because the exchange-rate variable in this study is measured in nominal terms, its SHAP contribution should not be interpreted as a direct measure of changes in real international price competitiveness. In Iran, where substantial domestic inflation occurred during 2000–2022, nominal depreciation may partly reflect differences in domestic and foreign price levels. The exchange-rate SHAP values therefore capture the predictive contribution of nominal exchange-rate movements conditional on the other variables included in the model, including inflation, rather than a pure real-exchange-rate effect.

The positive effect of exchange rate depreciation appears only when firms are able to maintain stable production costs and access necessary inputs. In contrast, excessive exchange rate volatility increases uncertainty, disrupts production planning, changes input prices, and reduces the ability of exporters to commit to long-term international contracts.

Therefore, the challenge for Iran's food industry is not necessarily the absolute level of the exchange rate, but rather the unpredictability and volatility of exchange rate changes. This distinction is particularly important because export-oriented industries require long-term planning, stable contracts, and predictable cost structures.

The Role of Technology and Machinery: A Supporting Rather Than Dominant Factor

The SHAP results place machinery imports below production capacity and productivity variables. This finding provides an important policy implication. Although technological modernization is necessary for industrial transformation, technology acquisition alone cannot generate competitiveness. The effectiveness of imported machinery depends on complementary capabilities, including:

1. managerial skills;
2. maintenance capabilities;
3. workforce expertise;
4. quality management systems;
5. market-oriented production strategies.

Therefore, technological transformation in Iran's food industry should not be interpreted merely as purchasing advanced equipment, but rather as developing the organizational capabilities required to effectively utilize technology.

Limited Direct Impact of Sanctions on Food Export Competitiveness

An important and potentially counterintuitive finding of this research is the relatively low SHAP contribution of sanctions intensity compared with domestic industrial variables.

This does not imply that sanctions have had no consequences. Sanctions have affected financial channels, investment flows, technology access, and international business relationships. However, the model suggests that within the food manufacturing sector, structural domestic factors have played a more decisive role in determining export competitiveness.

Several explanations can be considered. First, food products generally experience stable regional demand and are less dependent on highly specialized global supply chains compared with technology-intensive industries. Second, Iran's geographical proximity to neighboring markets provides relatively accessible export opportunities. Third, many barriers to export expansion originate from internal constraints, including production efficiency, market development, branding, and regulatory uncertainty.

Therefore, improving food export performance requires addressing internal transformation capabilities rather than relying solely on external explanations.

4.2.1. Strategic Implications Derived from Explainable AI

The SHAP analysis provides evidence that the transformation of Iran's food industry should follow a capability-oriented strategy. The results suggest that policy interventions should prioritize:

1. Increasing industrial productivity rather than only expanding production volume;
2. Strengthening agricultural–industrial value chains to increase domestic value creation;
3. Reducing economic uncertainty caused by excessive price and exchange rate fluctuations;
4. Improving technology absorption capacity instead of focusing only on machinery acquisition;

Developing export capabilities, including branding, marketing, and international market integration.

Overall, the explainable AI results demonstrate that the future competitiveness of Iran's food industry depends primarily on strengthening internal industrial capabilities. The findings provide the empirical foundation for the next analytical stage, where expert knowledge is incorporated to identify feasible transformation pathways and prioritize strategic interventions.

4.3. Expert-Based Artificial Intelligence Clustering and Identification of Industrial Transformation Pathways

While the machine learning and explainable AI analyses provide evidence regarding the historical drivers of export competitiveness, industrial transformation cannot be designed solely based on quantitative relationships. The transition of an industry toward a more competitive and globally integrated structure requires consideration of institutional conditions, managerial capabilities, market constraints, and practical experiences of industrial stakeholders.

Therefore, the third analytical stage incorporated expert knowledge through an Expert-Based Artificial Intelligence Clustering Framework. The purpose of this stage was not to replace empirical findings obtained from historical data, but rather to complement them by identifying feasible transformation directions from the perspective of industrial actors.

A total of 150 experts, including managers of food manufacturing firms, exporters, representatives of industry associations, specialists from the Iran Chamber of Commerce, government organizations, and relevant professional bodies, participated in the survey. The questionnaire was designed based on two sources: (1) the determinants identified by the XGBoost-SHAP analysis and (2) the challenges and transformation factors reported in previous industrial competitiveness studies. Thus, the ML-SHAP results served as an empirical input to the expert survey by identifying the economic, industrial, and technological factors with greater predictive relevance. Expert assessment was then used to examine how these factors, together with broader industry-specific capabilities, could be organized into feasible strategic configurations.

Respondents evaluated the importance and feasibility of different transformation capabilities, including production competitiveness, productivity improvement, technology adoption, market development, branding, export strategy, supply chain integration, regulatory environment, and macroeconomic stability.

After data standardization, the Self-Organizing Map (SOM) algorithm was applied to identify groups of experts with similar perceptions regarding industrial transformation priorities. Unlike conventional clustering methods, SOM is a neural network-based unsupervised learning technique capable of reducing multidimensional expert opinions into meaningful strategic clusters while preserving the relationships among observations (Kohonen, 2001). The final number of four clusters was determined based on the SOM clustering structure and the interpretability of the resulting expert groups. The four clusters represented distinct and internally coherent combinations of transformation priorities, including market development, productivity improvement, institutional stability, and technological upgrading. These clusters were therefore interpreted as transformation pathways because each represents a distinct strategic configuration of capabilities and priorities identified from expert assessments, rather than a predetermined classification.

The results identified four major strategic clusters representing different transformation pathways for Iran's food industry.

Table 5. Expert-based SOM clustering results for industrial transformation pathways

Cluster	Main strategic orientation	Share of experts (%)	Main characteristics
Cluster 1	Market-oriented transformation and internationalization	34.7	Emphasis on branding, international marketing, market access, export networks
Cluster 2	Productivity and industrial efficiency improvement	28.0	Focus on cost reduction, operational efficiency, quality improvement
Cluster 3	Institutional and policy transformation	21.3	Emphasis on regulatory stability, predictable policies, stakeholder participation
Cluster 4	Technology and innovation upgrading	16.0	Focus on digitalization, automation, Industry 4.0 capabilities

Source: Research Finding

4.3.1. Market Development and Branding as the Dominant Transformation Pathway

The largest expert cluster was associated with market-oriented transformation, accounting for approximately 35% of respondents. Experts identified weak international marketing capabilities, insufficient branding, limited presence in foreign distribution networks, and inadequate knowledge of target markets as among the most important barriers limiting Iran's food export expansion.

This finding provides an important complement to the machine learning results. Although the XGBoost model identified production capacity and productivity as the main historical drivers of exports, expert analysis reveals that converting production capability into sustainable export growth requires market-facing capabilities.

Iran possesses significant advantages in the food sector, including agricultural diversity, geographical proximity to major consumer markets, competitive production costs, and cultural compatibility with regional food preferences. However, these advantages have not been fully transformed into international market share due to limited branding strategies and weak international commercial networks.

Experts particularly emphasized that many Iranian food products compete mainly through price advantages rather than through recognized brands, differentiated products, and consumer loyalty. Therefore, future transformation strategies should move from a commodity-export approach toward a brand-based export model.

Table 6. Priority barriers identified by experts in market-oriented transformation

Barrier	Importance score (0–100)
Weak international branding	87.4
Limited foreign market development activities	84.9
Lack of international distribution networks	81.6
Insufficient export marketing capabilities	79.8
Limited product differentiation	76.5

Source: Research Finding

4.3.2. Productivity Enhancement and Industrial Efficiency Pathway

The second major cluster focused on improving productivity and operational efficiency. Approximately 28% of experts considered productivity improvement as the most critical pathway for strengthening competitiveness.

This result is highly consistent with the SHAP analysis, where food industry productivity emerged as one of the most influential determinants of export performance.

Experts emphasized that many food manufacturing firms face challenges related to:

1. inefficient production processes;
2. high material waste;
3. energy consumption intensity;
4. limited process optimization;
5. insufficient quality management systems.

The findings indicate that competitiveness cannot be achieved only through increasing production capacity. Instead, firms must improve their ability to produce internationally acceptable products at competitive costs.

This pathway suggests that industrial transformation policies should encourage process innovation, lean manufacturing practices, quality certification systems, and productivity-oriented investment.

Table 7. Productivity-related transformation priorities identified by experts

Priority area	Importance score (0–100)
Reduction of production costs	86.2
Improvement of production efficiency	84.7
Reduction of waste and losses	82.3
Quality management improvement	80.9
Supply chain optimization	78.6

Source: Research Finding

4.3.3. Institutional Stability and Policy Transformation Pathway

The third cluster emphasized the role of institutional and policy conditions. Approximately 21% of experts considered regulatory uncertainty and unstable economic policies among the most significant constraints affecting export competitiveness.

A recurring issue identified by experts was that Iranian food manufacturers face difficulties not necessarily because of the absolute level of production costs, but because of unpredictability in economic conditions.

In particular, experts highlighted:

1. exchange rate volatility;
2. sudden changes in export regulations;
3. inconsistent trade policies;
4. limited participation of industrial stakeholders in policy formulation.

The findings indicate that export competitiveness requires a stable business environment where firms can plan production, investment, and international contracts over longer periods. Experts also emphasized the importance of balancing domestic market considerations with export development objectives. In some cases, policies designed to protect domestic consumers may unintentionally restrict industrial export capacity by limiting access to inputs or creating uncertainty regarding export regulations.

A frequently mentioned example was the food processing sector's dependence on agricultural inputs. Experts argued that flexible input management policies, including the possibility of using imported raw materials when economically justified, could increase the competitiveness of processed food exports.

Table 8. Institutional barriers affecting food export competitiveness

Institutional constraint	Importance score (0–100)
Exchange rate instability	91.3
Sudden policy changes	88.7
Limited private-sector participation in policymaking	85.4
Export restrictions and administrative barriers	83.9
Difficulty in long-term planning	82.6

4.3.4. Technology and Digital Transformation Pathway

The fourth cluster identified technology upgrading and digital transformation as an important but relatively secondary pathway. Experts acknowledged the importance of automation, data-driven production management, artificial intelligence applications, and Industry 4.0 technologies. However, compared with market development and productivity improvement, technology adoption was perceived as a supporting capability rather than the primary transformation driver.

This finding is consistent with the machine learning results, where machinery imports had a positive but smaller contribution compared with production capacity and productivity.

The results suggest that technological transformation should be capability-driven rather than technology-driven. In other words, digital technologies create value only when integrated with improved management systems, skilled human resources, and market-oriented strategies.

4.4. Integrated Artificial Intelligence-Based Transformation Framework

The final analytical step integrates the findings from machine learning models, SHAP-based explainability analysis, and SOM expert clustering into a unified transformation framework. The quantitative models indicate that, within the fitted predictive framework, historical variation in export performance is most strongly represented by variables related to:

1. food manufacturing capacity;
2. industrial productivity;
3. agricultural value creation;
4. investment capability; and
5. macroeconomic conditions.

These results should be interpreted as identifying variables with substantial predictive relevance rather than establishing that these variables are the causal determinants of export competitiveness.The explainable AI analysis further clarifies that these factors operate through different mechanisms. Production capacity creates export potential, productivity determines competitiveness, agricultural value chains provide supply strength, and economic stability enables long-term planning. The expert-based SOM analysis adds the strategic dimension by identifying how these capabilities can be transformed into practical development pathways. The integration of empirical evidence and expert knowledge results in four interconnected transformation priorities.

Table 9. Integrated AI-based transformation pathways for Iran's food industry

Transformation pathway	Evidence source	Main policy actions
Export market and branding transformation	SOM + expert analysis	Develop national food brands, strengthen international marketing networks, improve market intelligence
Productivity-driven industrial upgrading	XGBoost + SHAP + SOM	Improve operational efficiency, reduce waste, implement quality systems
Institutional and policy transformation	Expert analysis + SHAP	Increase policy stability, strengthen industry participation, reduce uncertainty
Technology-enabled transformation	XGBoost + expert analysis	Promote digitalization, automation, and AI-based industrial management

Source: Research Finding

Overall, the integrated framework demonstrates that Iran's food industry transformation should not be interpreted as a simple expansion of production or a response to external restrictions. Instead, competitiveness requires a coordinated transition from a resource-based and production-oriented structure toward a capability-based, market-oriented, and technology-supported industrial system.

The main contribution of this research lies in moving beyond the traditional identification of export determinants toward the development of evidence-based transformation pathways. While previous studies have mainly focused on explaining what factors affect agricultural or food exports, the proposed AI-driven framework identifies how industrial capabilities can be prioritized and transformed into actionable development strategies.

Accordingly, the findings suggest that the future competitiveness of Iran's food industry depends less on isolated policy interventions and more on the simultaneous development of productive capabilities, international market integration, institutional stability, and adaptive technological capacity. This integrated perspective provides a practical roadmap for policymakers and industrial stakeholders seeking to enhance Iran's role in regional and global food markets.

5. Conclusion and Policy Implications

This study aimed to develop an artificial intelligence-based framework for identifying industrial transformation pathways in Iran's food manufacturing sector. Moving beyond conventional export studies that primarily focus on estimating the determinants of trade performance, this research integrated machine learning models, explainable artificial intelligence (SHAP), and expert-based neural clustering to identify both the historical drivers of competitiveness and the strategic capabilities required for future transformation.

The results demonstrate that export competitiveness in Iran's food industry is primarily associated with internal industrial capabilities rather than external factors alone. The machine-learning models identified food manufacturing output, industrial productivity, and agricultural value creation as the variables providing the strongest predictive contributions to the model's representation of export performance. The SHAP analysis further helped interpret how these variables contributed to individual model predictions and whether their contributions varied across observed conditions. These findings should not be interpreted as establishing causal determinants of export performance; rather, they identify empirical patterns and variables that are strongly informative within the fitted predictive framework.

The integration of expert knowledge through the SOM clustering approach complemented the quantitative findings by identifying feasible transformation priorities from the perspective of industrial stakeholders. The results highlight that Iran's food industry requires a transition from a production-oriented and commodity-based export structure toward a capability-based, market-oriented, and globally integrated manufacturing system. In particular, weaknesses in international branding, market development, policy stability, and productivity management were identified as major constraints preventing the full realization of the sector's export potential.

Based on the findings, the following policy implications are proposed:

- Shift industrial policy from production expansion toward productivity-driven competitiveness.Supporting efficiency improvement, process optimization, quality management systems, and waste reduction should become central components of food industry development strategies.
- Develop export-oriented market capabilities and national food brands. Given Iran's geographical advantages and production potential, greater emphasis should be placed on international marketing, branding strategies, foreign distribution networks, and market intelligence systems.
- Increase policy stability and strengthen private-sector participation in decision-making. Reducing regulatory uncertainty, avoiding sudden trade restrictions, and involving industrial stakeholders in policy formulation are essential for improving long-term investment and export planning.
- Promote agricultural–industrial value chain integration.Strengthening linkages between agricultural producers and food manufacturers can increase domestic value creation, improve supply reliability, and enhance the competitiveness of processed food exports.
- Adopt a capability-based approach to technological transformation.Digitalization, automation, and artificial intelligence applications should be accompanied by

improvements in managerial capabilities, workforce skills, and organizational readiness rather than focusing solely on technology acquisition.

- Design flexible trade and input policies to support export competitiveness. Policies governing access to production inputs should consider international competitiveness objectives and allow firms to optimize sourcing strategies when domestic constraints reduce export potential.

Overall, this research demonstrates that artificial intelligence can serve not only as a predictive instrument but also as a strategic decision-support mechanism for industrial transformation. The proposed framework provides a pathway for policymakers to move from identifying export problems toward designing evidence-based transformation strategies capable of enhancing Iran's position in regional and global food markets.

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