نشریه علمی
اقتصاد و توسعه کشاورزی
(علوم و صنایع کشاورزی)

جلد ۴۰ شماره ۲
سال ۱۴۰۵

شماره پیاپی ۷۱
شاپا: ۲۰۰۸-۴۷۲۲

عنوان مقالات

نشریه اقتصاد و توسعه کشاورزی

(علوم وصنایع کشاورزی)

با شماره پروانه 21/2015 ـــــ 68/4/11 و درجه علمی – پژوهشی شماره 26524 ـــــ 73/10/19 از وزارت علوم، تحقیقات و فناوری

جلد 40 شماره 2 تابستان1405

بر اساس مصوبه وزارت عتف از سال 1398، کلیه نشریات دارای درجه "علمی-پژوهشی" به نشریه "علمی" تغییر نام یافتند.

ناشر: دانشگاه فردوسی مشهد

نشانی: مشهد - کد پستی 91775 صندوق پستی 1163

دانشکده کشاورزی ــ دبیرخانه نشریات علمی ــ نشریه اقتصاد و توسعه کشاورزی

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این نشریه به صورت فصلنامه (4 شماره در سال) چاپ ومنتشر می شود.

بسم الله الرحمن الرحیم

مندرجات

Journal of Agricultural Economics & Development

Homepage: https://jead.um.ac.ir

Research Article

Vol. 40, No. 2, Summer 2026, p. 103-127

The Application of Data Mining in Analyzing Factors Affecting the Classification of Technical Efficiency of Wheat Farmers: A Study in Ahar County

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Received: 03 May 2025 Revised: 25 November 2025 Accepted: 02 December 2025 Available Online: 02 December 2025	**How to cite this article:** Vahedi, J., Ghahremanzadeh, M., Dashti, Gh., & Pakrooh, P. (2026). The application of data mining in analyzing factors affecting the classification of technical efficiency of wheat farmers: A Study in Ahar County. *Journal of Agricultural Economics & Development*, *40*(2), 103-127. https://doi.org/10.22067/jead.2025.93203.1349

Abstract

Ahar County, as one of the main agricultural production areas, produces a considerable share of rainfed wheat in East Azerbaijan Province. Improving technical efficiency (TE) in this region can have a significant impact on farmers' productivity and economic sustainability. Therefore, the present study was conducted with the aim of applying data mining to analyze the efficiency of rainfed wheat farmers in Ahar County. To this end, farmers' TE was calculated using Data Envelopment Analysis (DEA), and those with efficiency scores above the regional average (0.59) were classified as the high-efficiency group, while the rest were categorized as the low-efficiency group. Subsequently, t-tests and chi-square tests were employed to identify variables likely to influence TE. Machine learning algorithms, including logistic regression, support vector machines (SVM), k-nearest neighbors (k-NN), and random forest (RF), were then applied for classification and analysis of TE. The results indicated that logistic regression outperformed the other algorithms. The output of this algorithm revealed that factors such as herbicides, weed control, manure, land rental value, nitrate fertilizers, number of farm plots, pesticides, farmer's age, combined harvesting method, experience, household members with university education, seed procurement from the Agricultural Organization, and residence in rural areas have a positive effect on TE. Conversely, factors including mixed landownership (personal-rental), seed procurement from personal sources, and non-agricultural income exerted a negative influence on efficiency. Based on the findings, it is recommended that farmers receive necessary training on the optimal management of influential agricultural inputs, including herbicides, manure, nitrate fertilizers, and pesticides. Furthermore, policymakers are advised to enhance the motivation of farmers operating on rented lands by providing financial incentives and advisory services. The development of supportive programs for the supply of quality seeds and agricultural inputs through the Agricultural Jihad Organization is also proposed.

Keywords: Data mining, Machine learning, Technical efficiency, Wheat

https://doi.org/10.22067/jead.2025.93203.1349

Introduction

Optimal utilization of production resources in the agricultural sector is of paramount importance for feeding the growing global population. To address the challenges associated with meeting food demand, either the cultivated area must be expanded, or production efficiency must be maximized (Bahiraie *et al.*, 2020). These challenges generally encompass climate change, declining water resources, and limitations on available agricultural land, all of which adversely affect crop yields. Despite the constraints on agricultural production resources and the expanding needs of human societies, determining the efficiency of agricultural producers enables the quantification of the gap between the most efficient producers and others operating under identical technological conditions and with similar resource endowments. Such analysis can help identify weaknesses and strengths within production systems, thereby facilitating the design of more effective policies to enhance efficiency. Consequently, assessing farmers' efficiency can prove highly valuable in evaluating the suite of policies implemented in the agricultural sector (Davodnia *et al.*, 2023).

Numerous researchers have calculated the technical efficiency of wheat production and identified its determinants across various regions of Iran. Khodaverdizadeh *et al*. (2019) employed both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to estimate wheat production efficiency in Urmia County, identifying chemical fertilizers, pesticides, and agricultural machinery as significant factors influencing efficiency. Tanursaz *et al.* (2021), after calculating the technical efficiency of wheat farmers in Dezful County using SFA, applied the two-stage Heckman procedure to evaluate efficiency determinants. They reported an average technical efficiency of 0.78. They found that the adoption of conservation tillage technology, the ratio of conservation tillage machinery per village, farming experience, water consumption, and education level exerted positive and significant effects on efficiency. In contrast, labor input and distance from the village had negative and significant impacts. Ghasemi *et al.* (2023) investigated the technical, environmental, and economic efficiency of rainfed wheat farmers in Ahar County using SFA, calculating an average efficiency score of 0.66. Machinery, animal manure, chemical fertilizers, and pesticides were identified as key factors affecting efficiency. Naruei *et al.* (2024) examined the impact of climate change adaptation strategies on the technical efficiency of wheat farmers in the Sistan region using a modified endogenous stochastic frontier model. The results indicated that changes in land size, conservation tillage practices, and adjustments in planting dates had the strongest effects, while rainfall and the use of bio-fertilizers exhibited the weakest impacts. The average technical efficiency was estimated at 0.82.

Aryan *et al.* (2024) conducted a field experiment in eastern Afghanistan to determine the optimal timing of nitrogen fertilizer application for improving wheat technical efficiency. They found that average technical efficiency could increase by up to 68.6% with optimal nitrogen fertilizer management. Samson *et al*. (2024) employed SFA to assess the technical efficiency of wheat farmers in Jigawa State, Nigeria. Their results indicated that seed quality, chemical fertilizers, labor input, herbicides, and farming experience exerted positive effects on technical efficiency, whereas farmers' age, poor seed quality, inadequate road infrastructure, and limited access to financial resources and inputs had negative impacts. Girma *et al.* (2024) applied SFA to analyze wheat farmers' technical efficiency and identify its determinants in the Oromia region of Ethiopia, reporting an average technical efficiency score of 0.82. They found that education level, frequency of contact with agricultural extension agents, access to credit, farming experience, soil fertility, and participation in training programs contributed to higher efficiency, while non-farm income was associated with reduced efficiency.

Collectively, these studies demonstrate that environmental, economic, and social factors play crucial roles in determining technical efficiency, and identifying these determinants can facilitate improvements in farmers' yield.

Although these studies have employed methods such as stochastic frontier models and Hackman’s two-stage procedure to examine factors influencing technical efficiency, such approaches entail certain limitations, including dependence on restrictive statistical assumptions and an inability to uncover nonlinear and complex relationships among variables. These limitations can lead to inaccurate or misleading results, particularly when real-world data contains noise, missing values, and intricate causal relationships. Consequently, the necessity of adopting modern data mining and machine learning techniques becomes evident. Data mining, with its capacity to analyze complex datasets, enables the identification of hidden patterns and relationships among factors affecting technical efficiency. These methods not only provide higher accuracy and reliability in classifying farmers but also allow for more precise targeting of efficiency improvement strategies. Furthermore, data mining techniques offer the advantage of knowledge discovery directly from data without requiring stringent statistical assumptions, while validation techniques (e.g., cross-validation) help prevent overfitting. Nevertheless, research applying data mining and machine learning methods for the systematic classification and analysis of factors influencing farmers' technical efficiency remains scarce in the literature. Therefore, this study, as one of the first endeavors in this domain, seeks to deliver a comprehensive and precise analysis of the determinants of wheat technical efficiency by leveraging advanced data mining approaches.

Ahar County is recognized as one of the major hubs for wheat production in Iran. According to statistics from the East Azerbaijan Agricultural Jihad Organization (2022), in the Iranian calendar year 1400 (2021–2022), Ahar County accounted for approximately 10% of the province's total wheat-cultivated area, of which nearly 50,000 hectares (over 90%) were dedicated to rainfed wheat cultivation. Within the county's 52,000 hectares of arable land, 28,000 hectares are allocated to wheat production. This substantial cultivated area, significantly larger than that devoted to other crops in the region, highlights Ahar County's strategic importance in provincial wheat output. Nevertheless, given the relatively modest wheat yield per hectare in the area, further investigation into technical efficiency is warranted. Researching the economic dimensions of wheat production in Ahar County could therefore yield positive impacts on regional productivity. Moreover, the area's diversity in farming practices and levels of mechanization provides a suitable setting for testing the capabilities of data mining methods in identifying complex patterns influencing technical efficiency. In this context, the present study can serve as a robust framework for analyzing the current situation and identifying pathways to improve efficiency; its findings may assist farmers in making more informed decisions regarding the optimal utilization of production resources.

Based on the foregoing discussion, the primary objective of this study is to classify wheat farmers in Ahar County according to their level of technical efficiency and to systematically identify the most influential factors affecting efficiency by employing modern data mining and machine learning techniques. The fundamental innovation of the study lies in its status as one of the first studies in this domain to substitute traditional econometric and mathematical programming approaches with an analytical framework grounded in intelligent algorithms. Consequently, this research provides policymakers and farmers with a precise and practical framework for targeting efficiency improvement strategies based on real-world data. The study comparatively employs multiple data mining algorithms to deliver the most accurate and reliable model for identifying determinants of technical efficiency. Accordingly, the objective of this research is to apply data mining techniques to analyze the factors influencing the classification of technical efficiency among wheat farmers in Ahar County.

Materials and Methods

In this study, data mining techniques were employed to classify rainfed wheat-producing farmers in Ahar County based on their technical efficiency and to analyze the factors influencing it. Initially, the technical efficiency of wheat farmers was calculated using Data Envelopment Analysis (DEA) with an output-oriented approach under the assumption of variable returns to scale (VRS). Output was defined as wheat yield (kg), while inputs included area under cultivation (hectares), seed (kg), labor (person-days), and tractor usage (hours). DEA is a non-parametric method for evaluating the efficiency of decision-making units (DMUs) by comparing their yield based on inputs and outputs. This approach enables the simultaneous examination of multiple factors and facilitates the identification of both efficient and inefficient units (Cooper *et al.*, 2007).

Subsequently, wheat farmers were classified into two groups: high-efficiency farmers (those with efficiency scores above the regional average) and low-efficiency farmers (those with efficiency scores below the regional average). Next, considering variables potentially influencing their technical efficiency, the most appropriate machine learning algorithm was identified, one capable of assigning farmers to their respective efficiency class (high or low) with minimal classification error. In other words, for subsequent economic analyses, the algorithm was selected whose predicted classification of farmers into high- or low-efficiency groups showed the highest agreement with their actual efficiency-based classification derived from DEA calculations (For brevity, the phrases "above average" and "below average" will henceforth be omitted when referring to efficiency groups). The higher the algorithm's predictive accuracy, the greater the reliability of the ensuing economic analyses.

Data Mining

Data mining is the process of discovering patterns and hidden information from existing datasets (Shu & Ye, 2023). Within the knowledge discovery process, a dataset is first selected for examination. Subsequently, data cleaning operations, including noise removal, normalization, and standardization, are performed to enhance data quality. The next phase involves applying specific analytical techniques to the processed data, such as statistical tests (e.g., Student's t-test, chi-square test), visualization (to provide clear insights into patterns and relationships among variables), and classification (to identify and organize data into distinct groups based on similarities and shared characteristics). Appropriate algorithms are then selected to perform the intended analytical tasks. Finally, once suitable outputs are generated, the results are interpreted and evaluated (Gullo, 2015; McClendon & Meghanathan, 2015).

Machine Learning

Machine learning is a method by which computer systems learn through examples. A major category of machine learning algorithms is supervised learning, which operates by inferring patterns from labeled training data. In this approach, specific features or a set of features are provided to the algorithm to predict target outcomes. Among machine learning algorithms commonly employed in data mining analyses are classification algorithms (*Ngai et al.*, 2009; Bermudez *et al.*, 2011), whose objective is to construct models capable of predicting future outcomes by assigning database records to predefined classes based on specific criteria. Widely used tools for classification analysis include logistic regression, support vector machines (SVM), k-nearest neighbors (k-NN), and random forest (RF) (Sen *et al.*, 2020), each of which will be elaborated upon in the following sections.

Logistic Regression

Logistic regression is a supervised learning algorithm in which the model is trained on a labeled dataset comprising input data (features) and corresponding output labels (target class). It is a method employed for binary classification problems to predict the probability of a binary outcome, i.e., two possible classes, such as high-efficiency and low-efficiency farmers. This algorithm models the relationship between a dependent variable (typically binary; in this study, farmers categorized as high- or low-efficiency relative to the regional average) and one or more independent variables (which may encompass various data types, such as labor, cultivated area, and machinery) using a logistic function. The logistic function, also known as the sigmoid function, maps the output to a probability value ranging between 0 and 1 (Shetty *et al.*, 2022). Logistic regression operates based on the logistic (sigmoid) function, which is defined as Equation 1:

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (1)$$

Where z represents a linear combination of the features, as expressed in Equation (2) (James, 2013):

$$z = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_n x_n \quad (2)$$

In Equation (2), α_0 denotes the intercept, α_i represents the regression coefficients associated with the features, and x_i corresponds to the input features (independent variables). The output of the sigmoid function $\sigma(z)$ yields the probability of the dependent variable, for instance, $P(Y = 1|X) = \sigma(z)$. Ultimately, the regression coefficients can be estimated using maximum likelihood estimation, as formulated in Equation (3) (James, 2013).

$$P(Y = 0|X) = 1 - P(Y = 1|X) \quad (3)$$

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning algorithm designed for classification tasks that operates based on the identification of support vectors. This algorithm employs kernel functions and is particularly effective in pattern recognition and the classification of nonlinear data. SVM constructs a hyperplane to separate different classes. The hyperplane is iteratively optimized by the SVM algorithm with the objective of maximizing the margin between classes while minimizing classification errors (Sujatha & Mahalakshmi, 2020).

K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a machine learning algorithm that classifies new data points by comparing them with existing data points based on similarity metrics such as Euclidean distance. The algorithm identifies the k nearest neighbors (data points) to predict the class of a new observation. The accuracy of this algorithm depends on data quality, and it exhibits robustness against noise. The primary challenge in applying KNN lies in selecting an appropriate number of neighbors (k). KNN is widely employed in statistical estimation and pattern recognition based on proximity relationships among objects (Yuvalı *et al.*, 2022).

Random Forest (RF)

Random Forest (RF) is a modern ensemble method based on decision trees, comprising a collection of classification and regression trees. Each tree functions as an independent classifier for learning and prediction. Ultimately, the individual predictions are aggregated, typically through majority voting for classification or averaging for regression, to produce a final ensemble prediction that generally outperforms a single classifier (Xu & Yin, 2021).

Evaluation Metrics

Following the estimation of machine learning models, it is essential to evaluate the performance and predictive power of these algorithms using a set of quantitative metrics to ensure that the model adequately fulfills its intended tasks. The most important evaluation metrics include the confusion matrix, recall, accuracy, precision, F1-score, Cohen's kappa statistic, and the relative operating characteristic (ROC) curve. Each of these metrics reflects distinct aspects of model performance. Furthermore, employing this comprehensive set of metrics facilitates a more precise and nuanced analysis of prediction outcomes.

Confusion Matrix

The confusion matrix is a tabular layout that enables the visualization of a supervised learning algorithm's performance. Each column of the matrix represents the instances of a predicted class, while each row corresponds to the instances of an actual (true) class. All correct predictions are positioned along the diagonal of the table, allowing errors to be readily identified as non-zero values located off the diagonal. The confusion matrix for a binary classification problem is presented in Table 1 (Vahedi *et al*., 2024).

Table 1- Confusion matrix

		Predicted class	
		Particular class (C_1)	**Different class (C_2)**
Actual class	Particular class (C_1)	True positive (TP)	False negative (FN)
	Different class (C_2)	False positive (FP)	True negative (TN)

In the aforementioned confusion matrix, TP (True Positive) represents the number of samples that truly belong to class C_1 and are correctly predicted as C_1 by the model. TN (True Negative) denotes the number of samples that truly belong to class C_2 and are correctly predicted as C_2. FP (False Positive) refers to samples that do not belong to class C_1 but are erroneously classified as C_1, while FN (False Negative) indicates samples that do not belong to class C_2 but are mistakenly classified as C_2. Based on these definitions, a set of evaluation metrics, formulated in Equations (4) through (10), can be derived from the confusion matrix to assess the classification accuracy of the algorithms.

$$P = Actual\ positive = TP + FN \quad (4)$$

$$P^1 = Predicted\ positive = TP + FP \quad (5)$$

$$N = Actual\ negetive = FP + TN \quad (6)$$

$$N^1 = Predicted\ negetive = FN + TN \quad (7)$$

$$TP\ rate = Sensitivity = TP/P = Recall \quad (8)$$

$$Precision = TP/P^1 \quad (9)$$

$$Accuracy = (TP + TN/P + N) = TP/(P + N) + TN/(P + N) = TP/P \times P/(P + N) + TN/N \times N/(P + N) = Sensitivity \times P/(P + N) + Specificity \times N/(P + N) \quad (10)$$

where, P denotes the actual positive values, P^1 represents the predicted positive values, N indicates the actual negative values, and N^1 refers to the predicted negative values. Recall is defined as the ratio of correctly predicted positive instances to the total number of actual positives in the class, while precision represents the ratio of correctly predicted positives to the total number of predicted positives (e.g., the number of high-efficiency farmers correctly predicted as high-efficiency divided by the total number of farmers predicted as high-efficiency). Finally, Accuracy is the ratio of the total number of correct predictions to the total number of predictions (Hackeling, 2017). In certain cases, Recall and Precision do not increase simultaneously and may fail to enhance overall classification accuracy. To address this limitation, the F1-score is employed alongside the aforementioned metrics. This metric represents the harmonic mean of recall and precision, thereby providing a balanced assessment of classification performance. The F1-score can be calculated as expressed in Equation (11) (Khan *et al*., 2020):

$$F1 - score = 2\,\frac{(Recall \times Precision)}{(Recall + Precision)} \quad (11)$$

Cohen's Kappa

Cohen's Kappa statistic is commonly employed for binary classification problems. The lowest possible value of this metric is –1, while the highest (optimal) value is +1. Based on the cells of a 2×2 confusion matrix, Cohen's Kappa is defined as Equation (12) (Warrens, 2008):

$$\kappa = \frac{2.(TP.TN - FP.FN)}{(TP+FP).(FP+TN)+(TP+FN).(FN+TN)} \quad (12)$$

Relative Operating Characteristic (ROC) Curve

The Receiver Operating Characteristic (ROC) curve is a graphical tool used to evaluate the performance of a binary classification model. This curve illustrates the relationship between two key metrics: sensitivity (true positive rate) and the false positive rate. Accordingly, the area under the curve (AUC), also referred to as the discrimination measure, indicates the model's ability to distinguish between classes, as formulated in Equation (13) (Hordri *et al*., 2018).

$$AUC = \frac{1}{2}.(Sensitivity + Specificity) \quad (13)$$

In this study, 5-fold cross-validation is employed. This procedure divides the dataset into five subsets of equal size. Subsequently, one subset is used for testing while the remaining four subsets are utilized for model training. This process is repeated iteratively until each subset has been used once as the test set (Otunaiya & Muhammad, 2019).

In this research, the grid search method was employed to optimize machine learning models and precisely determine hyperparameters. Hyperparameters are values specified prior to the model training process and exert a considerable influence on the model's final performance. These parameters include values such as the number of trees in a random forest. The grid search method enables a systematic exploration of a predefined hyperparameter space; combined with cross-validation, it facilitates the selection of the optimal hyperparameter combination for the model, thereby achieving enhanced predictive accuracy (Ranjan *et al*., 2019). Data were collected through simple random sampling via face-to-face interviews and structured questionnaires administered to 223 rainfed wheat producers in Ahar County during the Iranian calendar year 1400 (2021–2022). The conceptual framework of the present research is illustrated in Fig. 1.

Results and Discussion

In this study, the technical efficiency of rainfed wheat-producing farmers in Ahar County was initially calculated using Data Envelopment Analysis (DEA), with its frequency distribution reported in Table 2. The results present a clear depiction of efficiency dispersion among farmers. According to these data, a substantial proportion of farmers, 44.4%, fall within the lowest efficiency tier, scoring below 50%. This pattern becomes more pronounced when incorporating farmers in the 51–70% efficiency range, who constitute 25.6% of the sample; collectively, 70% of all sampled farmers, i.e., the majority continue their operations at an efficiency level of 70% or lower. In contrast, the share of farmers achieving higher efficiency levels is considerably limited. Only 13.4% of farmers fall within the 71–90% range, while the highest efficiency tier (above 90%) is attained by merely 16.6% of farmers. The cumulative frequency distribution further corroborates this observation, revealing that 186 farmers, equivalent to 83.4% of the total sample achieved scores of 90% or below. Consequently, it can be inferred that the efficiency distribution among wheat farmers in Ahar County is skewed toward low and medium levels, thereby revealing substantial potential for enhancing productivity and optimizing resource management across a significant portion of this agricultural community.

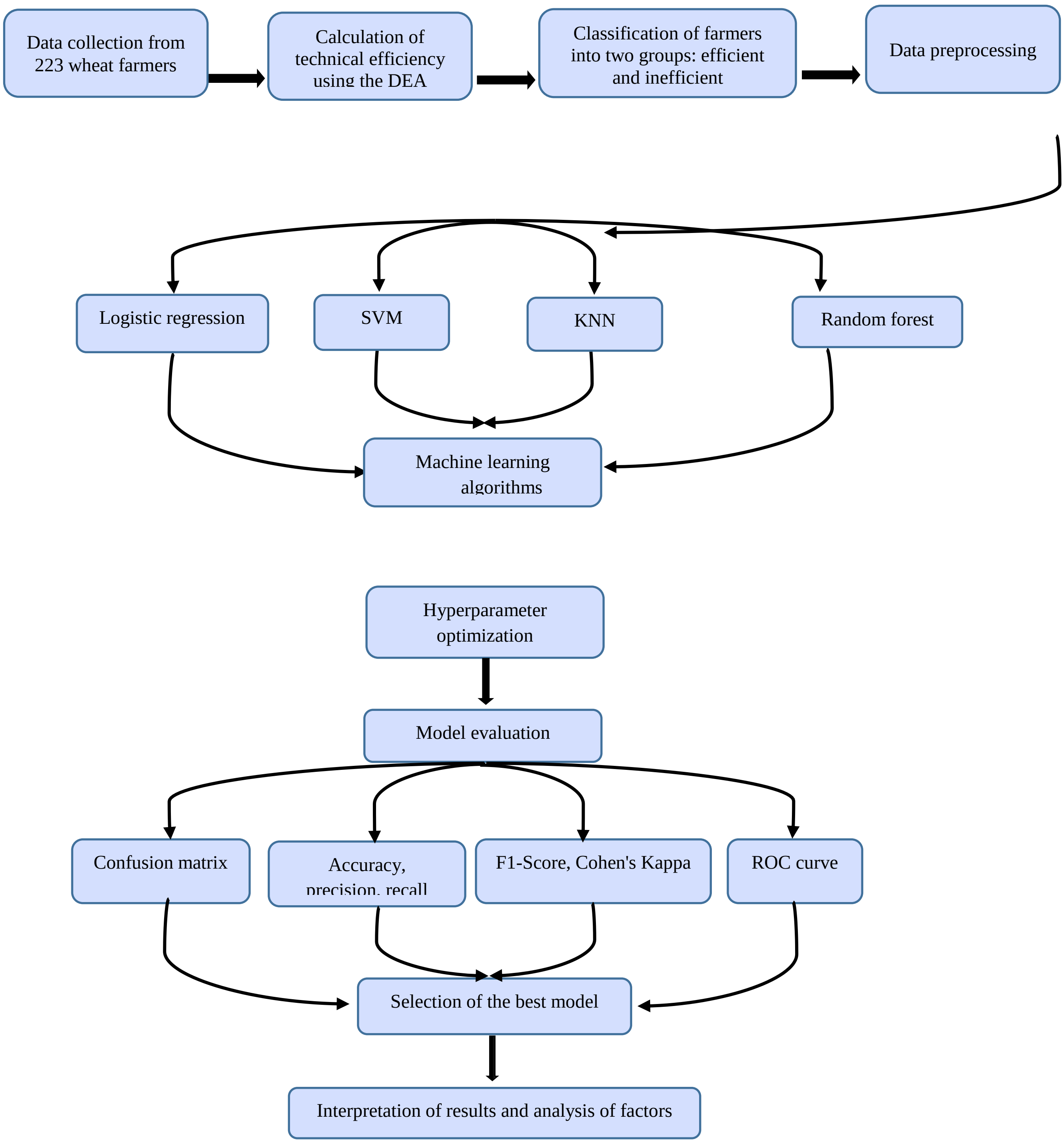

Figure 1- Conceptual framework of study

According to Table 2, the mean technical efficiency of wheat growers in the region equals 0.59, indicating that, on average, farmers utilize only 59% of their production potential. In other words, with their current input levels, farmers could potentially increase output by 41%. The standard deviation of 0.24 further confirms the existence of a relatively pronounced gap in technical efficiency levels among farmers; while some operate near optimal performance, others face considerable inefficiency. The wide efficiency ranges from 0.22 to 1.00 (a difference of 0.78 units) reflects a substantial yield disparity within the region's rainfed wheat production system. This finding reveals that at least one farmer in the sample utilizes merely 22% of their production potential, whereas others have attained full efficiency (100%). Such a marked disparity clearly underscores the presence of structural deficiencies, unequal access to inputs, gaps in technical and technological knowledge, and variations in farm management quality among farmers. These conditions create an ideal setting for applying data mining techniques to identify the key factors driving this wide efficiency gap and to design differentiated policy interventions tailored to each farmer group.

To scientifically address this extensive heterogeneity and systematically analyze the factors underlying the efficiency gap, it was necessary to classify farmers into distinct and meaningful groups. Accordingly, in the next step and to prepare the data for analysis using machine learning algorithms, farmers with technical efficiency below the regional average were assigned to group zero (low-efficiency farmers), while those with efficiency above the average were placed in group one (high-efficiency farmers). This binary classification formed the basis for implementing classification algorithms in the subsequent phase of the research.

Five types of data have been used in this research: continuous, countable, nominal, dummy, and ordinal. Prior to implementing machine learning models, an analytical examination of these variables was conducted. Table 3 presents the mean and median values of individual and economic characteristics for low-efficiency and high-efficiency farmers in Ahar County. The results indicate statistically significant differences between the two farmer groups across various dimensions, including cultivated area, land rental value, seed quantity,

Table 2- Frequency distribution of technical efficiency of wheat farmers in Ahar county

Technical Efficiency Range	Frequency	Frequency Percentage	Cumulative Frequency
<50	99	44.4	99
51-70	57	25.6	156
71-90	30	13.4	186
>90	37	16.6	223
Mean	0.59		
Std.ev	0.24		
Minimum	0.22		
Maximum	1		

Labor input, tractor usage, nitrate fertilizer consumption, age, and farming experience[1].According to Table 3, the average consumption of all inputs is notably lower among low-efficiency farmers compared to their high-efficiency counterparts. Additionally, high-efficiency farmers are older and have more farming experience relative to inefficient farmers.

The median values further reveal that the cultivated area for 50% of low-efficiency farmers is less than 2 hectares, whereas this figure amounts to 7.3 hectares for high-efficiency farmers. Similarly, the median values of other variables exhibit considerable disparities between the two farmer groups. Moreover, the mean values for high-efficiency farmers closely approximate their respective medians, a pattern also observed among low-efficiency farmers. This proximity between means and medians in both groups may indicate a relatively symmetric distribution of inputs within each category. Overall, it appears that one of the principal factors underlying

1 - Given that the study focuses on rainfed wheat production, wheat output in the region is entirely dependent on precipitation. For this reason, water as an input variable was not considered in the analysis.

efficiency differences among regional farmers is their varying level of access to agricultural inputs.

Table 3- Mean and median of some individual and economic variables in efficient and inefficient farmers

Inputs	Mean		Median	
	Low-efficiency farmers	High-efficiency farmers	Low-efficiency farmers	High-efficiency farmers
Land (hectar)	2.2	7.8	2	7.3
Rental value of lands (million toman)	1.9	5.8	1.2	5
Seed (kg)	481	1707	420	1500
Labor (man-day)	12	33	10	25
Tractor (hour)	22	59	18	50
Nitrate fertilizer	223	455	250	350
Age (year)	48	54	48	56
Experience (year)	32	40	30	40

Fig. 2 illustrates the distribution of continuous variables, including nitrate fertilizer consumption, agricultural land rental value, age, and farming experience. Variables previously utilized in the technical efficiency calculations, namely cultivated area, seed quantity, labor input, and tractor usage, were intentionally excluded from this visualization. According to Fig. 2, nitrate fertilizer consumption exhibits a pronounced peak at 250 kilograms, which may be attributable to the presence of outlier observations. Such outliers can undermine the validity of statistical tests and potentially compromise the reliability of machine learning model outcomes. Therefore, it is essential to identify these observations and mitigate their adverse effects. To this end, Fig. 3 employs box plots for outlier detection. For instance, the box plot for land rental value reveals that most observations fall below 10 million Iranian Tomans, with 8 outliers appearing above this threshold. The nitrate fertilizer variable contains 22 outlier observations, whereas age and farming experience display relatively uniform distributions without significant outliers. Following the identification of outliers in certain variables, this study addresses the issue through data standardization. Specifically, standardization was performed by subtracting the mean from each observation and subsequently dividing the result by the variable's standard deviation.

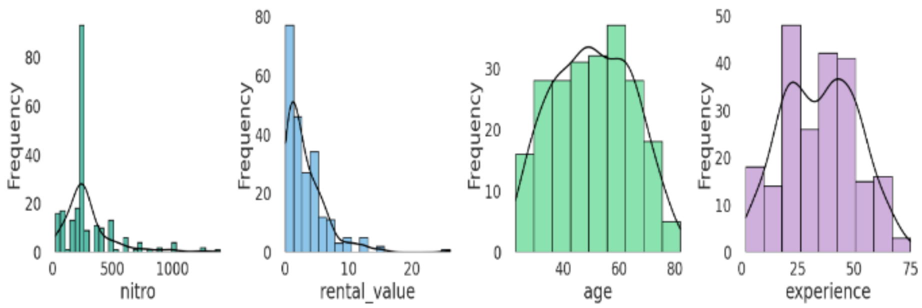

Figure 2- Probability distribution of continuous variables

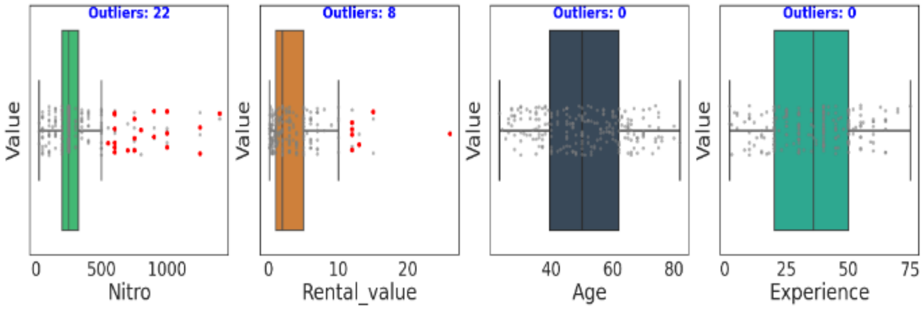

Figure 3- Box plot to identify outliers

Given that one of the primary objectives during the data preprocessing stage is the selection of appropriate variables for the final model, it is essential at this juncture to determine which continuous variables exert a significant influence on the target variable (i.e., classification into high-efficiency versus low-efficiency farmers). To this end, Student's *t*-test was employed to compare the means between the two groups, with results reported in Table 4. According to Table 4, incorporating the continuous variables into machine learning models is statistically justified. For instance, regarding nitrate fertilizer usage, the mean for group zero (low-efficiency farmers) equals 223 kilograms, whereas the mean for group one (high-efficiency farmers) amounts to 445 kilograms. This substantial difference suggests that variations in nitrate fertilizer application may indeed influence the status of the target variable, thereby supporting its inclusion as a predictive feature in the classification models.

Descriptive statistics for countable variables, including the number of farm plots, household members, and household members with university education, are reported in Table 5. The mean number of farm plots equals 11 with a standard deviation of 9, indicating substantial variability in land fragmentation among farmers. The average household size is 5 members with a standard deviation of 2, suggesting relative stability in this variable. Regarding household members with university education, a mean of 0.6 and a standard deviation of 0.9 reveal that only a subset of households includes university-educated members. The minimum and maximum values of these variables further confirm considerable dispersion in both household structure and landholding patterns across the sample.

Table 4- T-test results between continuous and target variables

Variable	t-statistic	P-value	Mean of group 0	Mean of group 1	Result
Nitrate fertilizer (kg)	-6.96	7.04	223	455	Reject
Rental value of lands (million toman)	-7.76	1.33	1.9	5.8	Reject
Age (year)	-2.99	0.003	48	54	Reject
Experience (year)	-3.19	0.001	32	40	Reject

Table 5- Descriptive statistics of countable variables

Variable	Mean	Std.dev	Minimum	Maximum
Familly members (plot)	11	9	1	40
Familly members (person)	5	2	1	12
Familly members with university education (person)	0.6	0.9	0	4

Subsequently, similar to the continuous variables, the influence of countable variables on the target variable was examined using Student's *t*-test, with results presented in Table 6. The null hypothesis of this test posits no significant difference in the means between the two farmer groups i.e., no significant effect of the countable variable on the target variable.

According to the results in Table 6, the null hypothesis is rejected for the variables "number of farm plots" and "household members with university education," indicating statistically significant differences between high- and low-efficiency farmer groups. Consequently, these two variables were incorporated into the machine learning modeling process. Furthermore, box plot visualizations for these variables revealed the presence of outliers; therefore, standardization was applied to mitigate their potential adverse effects on model performance.

Table 6- T-test results between countable and target variables

Variable	T-statistic	P-value	Mean of group 0	Mean of group 1	Result
Farm plots (plot)	-11.05	0.00	7.20	20.09	Reject
Family members (person)	-1.20	0.22	5.12	5.49	Accept
Family members with university education (person)	-2.65	0.00	0.46	0.84	Reject

Fig. 4 illustrates the distribution of farmers across nominal variables. Regarding residence location, the majority of observations correspond to farmers residing in rural villages. Most farmers source their seeds from their own farms, underscoring the significance of local resources in seed provision. A substantial proportion of farmers cultivate wheat on lands fully owned by themselves. The chart for the harvest method variable clearly indicates farmers' pronounced yield for mechanized harvesting techniques. Furthermore, the majority of farmers employed mowers for wheat harvesting. A primary reason for this choice is the steep slope of certain fields combined with the mower's superior performance on uneven terrain, which enhances harvest efficiency. Additionally, the relatively small size of farms and the impracticality of deploying larger combine harvesters render the mower a more feasible option. The mower's adaptability to diverse field conditions and its more effective operation during harvest, particularly in farms with limited area, enables farmers to improve both productivity and harvest quality.

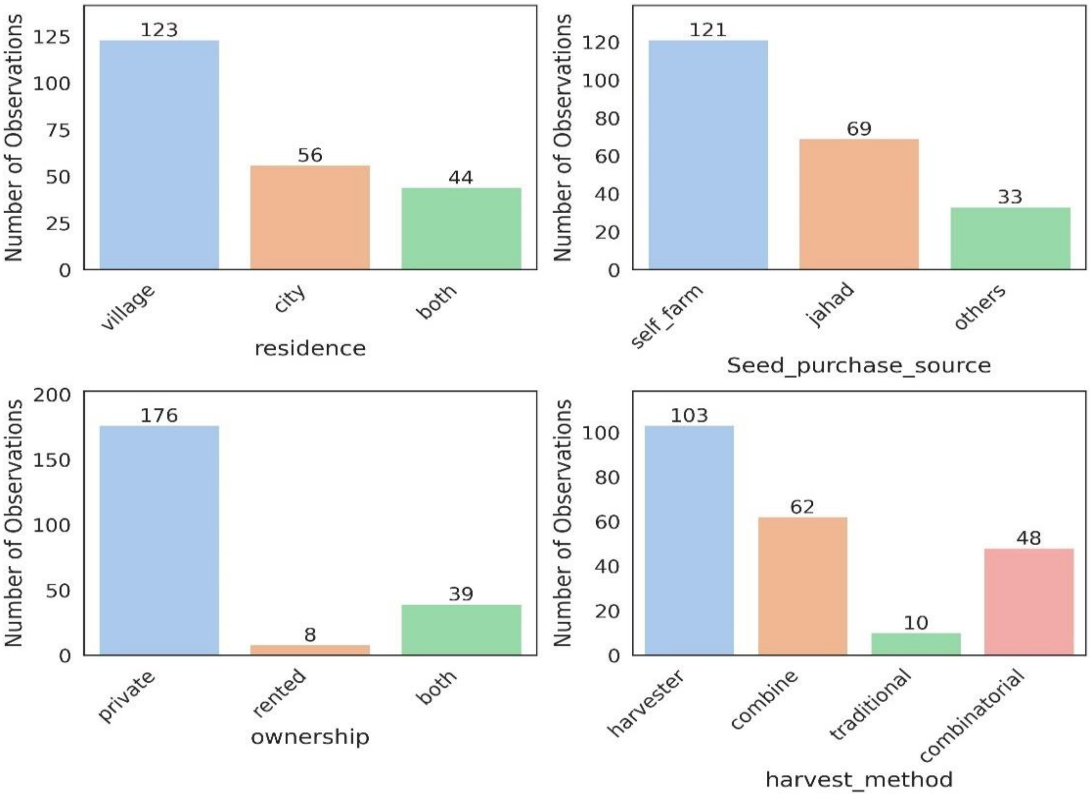

Figure 4- Distribution of farmers based on nominal variables

To incorporate nominal variables into machine learning models, it is necessary to convert them into dummy (binary) variables. Specifically, each category within a nominal variable must be transformed into a separate binary variable. Consequently, three dummy variables were created for each of the following nominal variables: residence location, seed source, and land ownership type. For the harvest method variable, four dummy variables were designed. Additional dummy variables included indicators for performi

ng contour plowing (perpendicular to slope), having off-farm income, and the use (or non-use) of certain variable inputs such as manure, herbicides, and pesticides.

To select dummy variables with a statistically significant influence on the target variable, a chi-square test was conducted, with results presented in Table 7. For instance, the null hypothesis for the rural–urban residence variable was accepted at a *P*-value of 0.07, indicating that residence location does not exert a statistically significant effect on the target variable. Overall, based on Table 7, the null hypothesis of the chi-square test was accepted for the following variables: rural–urban residence, urban residence, seed source (others), seed source (self-produced), land ownership (personal), land ownership (leased), harvest method (combine), harvest method (mower), harvest method (traditional), and contour plowing. In other words, these variables do not demonstrate a statistically significant impact on the target variable and were therefore excluded from the final modeling stage performed by the machine learning algorithms.

Table 7- Results of the Chi-square test between dummy and target variables

Variable	Chi-square statistic	P-value	Result
Residence_both	3.09	0.07	Accept
Residence_city	1.59	0.20	Accept
Residence_village	7.02	0.00	Reject
Seed_purchase_source_jahad	13.52	0.00	Reject
Seed_purchase_source_others	1.76	0.18	Accept
Seed_purchase_source_self_farm	5.39	0.02	Accept
Ownership_both[1]	6.39	0.01	Reject
Ownership_private	3.20	0.07	Accept
Ownership_rented	0.73	0.39	Accept
Harvest_method_combinatorial	5.55	0.01	Reject
Harvest_method_combine	0.79	0.37	Accept
Harvest_method_harvester	0.12	0.72	Accept
Harvest_method_traditional	1.49	0.22	Accept
Vertical_plow	2.10	0.14	Accept
Nonfarm_income	7.45	0.00	Reject
Manure	6.86	0.00	Reject
Herb	15.12	0.00	Reject
Pest	22.00	2.72	Reject

Ordinal variables in this study include education level, timeliness of agricultural operations, input availability, land slope, weed control practices, and the extent of damage caused by the sunn pest (Eurygaster integriceps). Fig. 5 illustrates the distribution of farmers across these ordinal variables. According to the figure, the reluctance of individuals with higher educational attainment to continue farming is clearly evident. Conversely, the majority of farmers carry out agricultural operations in a timely manner, reflecting a strong commitment to adhering to appropriate scheduling in farm management practices. The chart depicting input availability reveals considerable disparities in farmers' access to essential agricultural resources. According to the weed control distribution, the largest number of farmers, 134 observations fall into the "low" category, indicating that a substantial proportion of farmers do not implement effective practical measures for weed management. Finally, the graph illustrating sunn pest damage shows that only 71 surveyed individuals reported no damage from this pest, while the remaining farmers experienced varying degrees of crop loss attributable to sunn pest infestation.

Table 8 presents the results of the chi-square test conducted to select ordinal variables with a significant influence on the target variable's status. According to Table 8, weed control emerges as the sole ordinal variable that will be incorporated into the machine learning models. As previously mentioned in the Materials and Methods section, the present study employed four algorithms: logistic regression, support vector machine (SVM), k-nearest neighbors (KNN), and random forest (RF). In the initial step, considering default hyperparameters and utilizing 5-fold cross-validation, the accuracy of the models was compared, with results reported in Table 9. Here, the average accuracy of each algorithm is displayed alongside accuracies corresponding to different values of *k*. Logistic regression achieved an average accuracy of 88.7%, establishing it as the top-performing algorithm at this stage.

1- In the study area, it is common practice for an individual, in addition to cultivating land they own, to also rent and cultivate several other plots if possible.

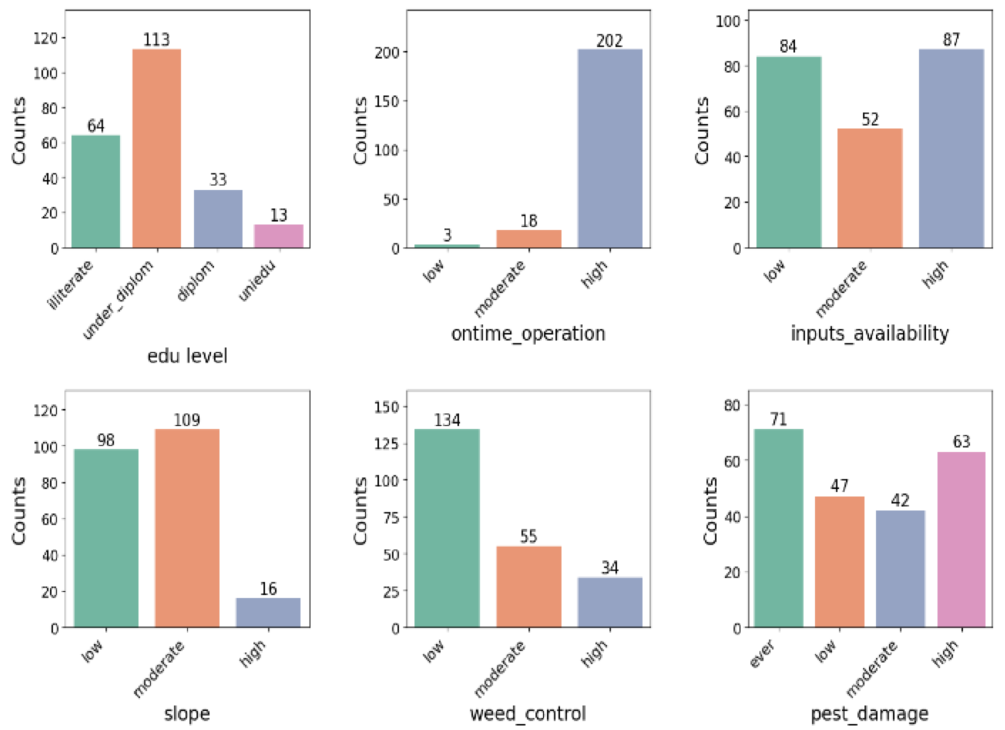

Figure 5- Distribution of farmers based on ordinal variables

Table 8- Chi-square test between ordinal and target variables

Variable	Chi-square statistic	P-value	Result
Edu level	2.20	0.53	Accept
Ontime_operation	20.47	3.58	Accept
Inputs_availability	1.45	0.48	Accept
Slope	4.84	0.08	Accept
Weed_control	5.81	0.05	Reject
Pest_damage	5.77	0.12	Accept

Table 9- The comparison of the algorithms based on accuracy statistics

Algorithm	K=1	K=2	K=3	K=4	K=5	Average accuracy
LogisticRegression	0.844	0.866	0.933	0.909	0.886	88.7%
SVC	0.822	0.866	0.911	0.886	0.886	87.4%
KNN	0.888	0.822	0.888	0.886	0.909	87.7%
Random Forest	0.800	0.866	0.888	0.954	0.909	88.3%

To further validate the employed algorithms, they were re-evaluated using various hyperparameters, and optimal parameters for each algorithm were determined using the GridSearchCV method. The resulting outcomes are presented in Table 10. This table includes the best configurations and the highest accuracy achieved by each algorithm. Overall, Table 10 highlights the importance of proper hyperparameter selection in enhancing algorithm accuracy and the overall performance of machine learning models. Each algorithm yielded different results with its specific settings, which can aid in selecting the most suitable algorithm. The Logistic Regression algorithm, with hyperparameter C=1 and maximum iterations (max_iter=10000), achieved an accuracy of 88.7%, indicating superior performance compared to the other algorithms.

Table 10- GridSearchCV results for determining optimal hyperparameters

Algorithm	Highest accuracy	The best hyperparameters
LogisticRegression (max-iter=10000)	0.887	C=1
SVC	0.886	C=5, kernel=sigmoid
KNN	0.879	N_beighbors=5
RandomForestClassifier (random-state=0)	0.883	N_estimators=50

Furthermore, to substantiate the superiority of the selected algorithm, the confusion matrix results are presented in Fig. 6. As observed, the Logistic Regression algorithm correctly classified 26 individuals within the low-efficiency farmer group as low-efficiency farmers, misclassifying only 2 individuals into the high-efficiency farmer group. With regard to high-efficiency farmers, the algorithm accurately predicted 15 individuals as high-efficiency farmers while erroneously assigning 2 individuals to the low-efficiency group. The Support Vector Machine (SVM) algorithm misclassified only one individual in the low-efficiency farmer category, whereas the K-Nearest Neighbors (KNN) algorithm correctly assigned all 28 individuals to their true low-efficiency class. However, concerning the high-efficiency farmer group, both algorithms exhibited suboptimal performance, each misclassifying 6 individuals. Finally, the Random Forest algorithm produced one misclassification in the low-efficiency group and four misclassifications in the high-efficiency group. Overall, analysis of the confusion matrix corroborates the relative superiority of the Logistic Regression algorithm compared to the other evaluated classifiers.

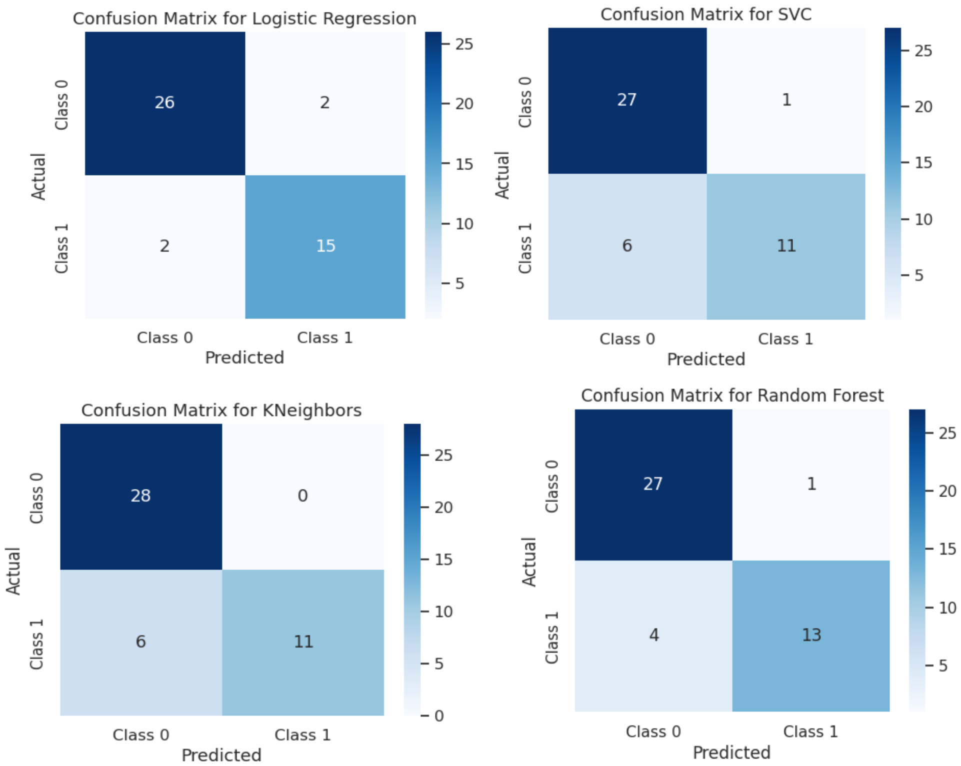

Figure 6- Confusion matrices from the research algorithms

Table 11 presents a comparative analysis of the prediction performance of various machine learning algorithms, reporting distinct metrics for each algorithm across the two classes of low-efficiency and high-efficiency farmers. To this end, the evaluation metrics, including precision, recall, F1-score, accuracy, and Cohen's Kappa, were computed based on the confusion matrix. According to the results in Table 11, the Logistic Regression algorithm demonstrates superior predictive performance overall compared to the other algorithms under consideration.

Table 11- Comparing the predictability of machine learning algorithms

Algorithm	Class	Precision	Recall	F1-score	Accuracy	Cohen's Kappa
LR	Non-efficient	0.93	0.93	0.93	0.91	0.81
	Efficient	0.88	0.88	0.88		
SVC	Non-efficient	0.82	0.96	0.89	0.84	0.64
	Efficient	0.92	0.65	0.76		
KNeighbors	Non-efficient	0.82	1.00	0.90	0.86	0.69
	Efficient	1.00	0.65	0.79		
RF	Non-efficient	0.87	0.96	0.92	0.88	0.75
	Efficient	0.93	0.76	0.84		

Additionally, to compare the predictive power of the algorithms, ROC curves can be plotted as illustrated in Fig. 7. The horizontal axis of the plot represents the false positive rate (FPR), while the vertical axis denotes the true positive rate (TPR). According to Fig. 7, an algorithm whose ROC curve approaches the coordinate (1,1) more closely and exhibits a higher area under the curve (AUC) possesses superior predictive capability. The Logistic Regression algorithm, with an AUC of 0.98, demonstrates the best performance in identifying positive cases, thereby outperforming the other algorithms. The Support Vector Machine (SVM) algorithm, with an AUC of 0.95, ranks second, indicating high accuracy, albeit marginally lower than that of Logistic Regression.

The K-Nearest Neighbors and Random Forest algorithms follow in subsequent ranks, with AUC values of 0.91 and 0.93, respectively. Finally, the presence of a 45-degree diagonal line representing random chance underscores that algorithms exhibiting curves above this baseline demonstrate superior capability in identifying positive cases. In this context, Logistic Regression exhibits notably superior performance, with its ROC curve positioned distinctly above the diagonal reference line.

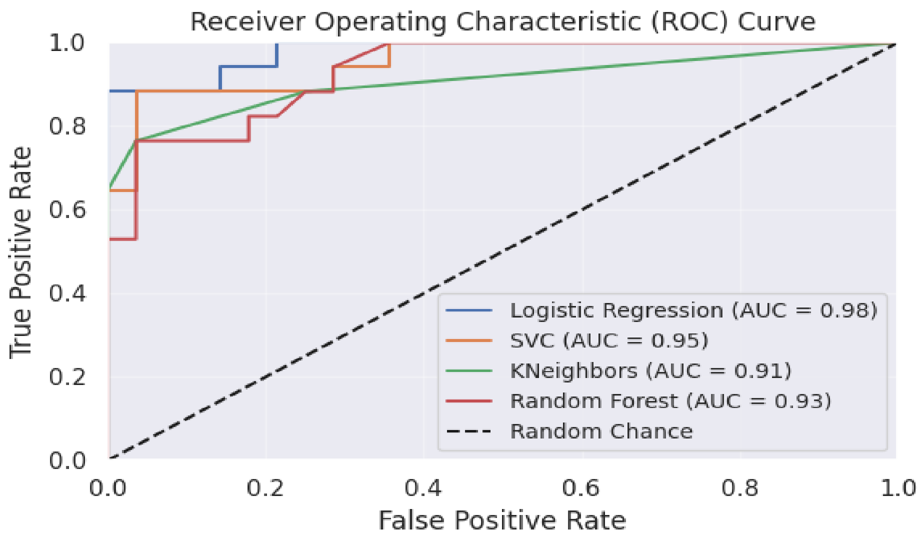

Figure 7- Comparison of the performance of machine learning algorithms using the ROC curve

Table 12 employs the Logistic Regression algorithm to examine the factors influencing the technical efficiency of rain-fed wheat producers in Ahar County. The table comprises two principal columns presenting the regression coefficients and corresponding odds ratios for each explanatory variable. According to the results, variables including herbicide application, weed control practices, manure usage, rental value of wheat cropland, nitrate fertilizer application, number of farm plots, pesticide use, farmer age, combined harvesting method, farming experience, presence of household members with university education, seed procurement from the Agricultural Jihad Organization, and rural residence exert a positive and statistically significant effect on technical efficiency levels. Conversely, mixed ownership status of cropland (personal-rental combination), seed procurement from personal sources, and possession of non-farm income demonstrate negative effects on technical efficiency.

Given that the estimated coefficients in this logistic regression model lack direct intuitive interpretation, odds ratios were computed to facilitate meaningful inference. For instance, the odds ratio of 2.927 for herbicide application indicates that farmers who utilize herbicides are approximately three times more likely to achieve improvements in technical efficiency compared to those who do not. Optimal herbicide application at various crop growth stages effectively suppresses weed competition, thereby reducing resource rivalry with wheat plants and enhancing both yield quantity and grain quality. Effective weed management enables wheat plants to more efficiently absorb rainfall and soil nutrients, ultimately contributing to increased productivity and improved technical efficiency. The application of manure, as a natural source of essential nutrients enhances soil structure and fertility, supporting the nutritional requirements of wheat throughout its growth cycle. A higher rental value of wheat cropland may reflect superior soil quality and greater production potential, while also enabling the adoption of modern agronomic and managerial practices that positively influence technical efficiency. Nitrate fertilizer application contributes to elevated soil nitrogen levels, promoting robust plant growth and higher grain yields. Furthermore, farmers cultivating multiple land plots can better mitigate risks associated with adverse weather conditions or pest outbreaks by diversifying spatial exposure and implementing more flexible, optimized strategies for planting and harvesting operations.

The application of pesticides enables farmers to mitigate pest damage to crops, thereby enhancing agricultural productivity. Nevertheless, to ensure long-term sustainability, adopting environmentally conscious approaches, such as Integrated Pest Management (IPM), is essential to minimize adverse ecological impacts while maintaining effective pest control.

Farmer age can serve as a proxy for accumulated agricultural experience in cultivation and farm management practices. Older farmers typically possess greater experiential knowledge in managing agricultural operations and selecting effective agronomic techniques, which may contribute to enhanced technical efficiency. Agricultural experience enables farmers to make more informed decisions regarding optimal farming practices and to utilize resources more efficiently. Experienced farmers tend to adopt superior strategies for addressing agronomic challenges such as adapting to variable climatic conditions, optimizing input allocation, and implementing timely interventions, thereby fostering improvements in technical efficiency. This accumulated practical knowledge, developed over years of engagement with farming systems, represents a valuable intangible asset that positively influences production outcomes and operational performance.

The adoption of combined harvesting methods can enhance efficiency throughout the crop harvesting process. Such approaches enable farmers to optimize the utilization of time and resources, resulting in greater crop recovery and elevated technical efficiency. The presence of university-educated household members within farming families can contribute to the advancement of agricultural management knowledge and skills. These individuals, leveraging their formal education and expertise, can assist in refining farming strategies and decision-making processes, thereby fostering improvements in technical efficiency. Procurement of seeds from reputable agricultural institutions, such as the Agricultural Jihad Organization, facilitates access to high-quality, pest-resistant seed varieties. This practice directly contributes to enhanced crop performance and yield stability through improved genetic traits and reduced vulnerability to biotic stresses. Residence in rural areas serves as a significant enabler for the timely execution of agronomic operations. Proximity to farmland allows farmers to respond promptly to critical cultivation windows, while also facilitating greater accessibility to local resources, extension services, and emerging agricultural technologies, all of which collectively support the enhancement of technical efficiency in farming systems.

Regarding factors exerting negative influences on technical efficiency, mixed land ownership (personal and rental) warrants particular attention. Under this arrangement, farmers may exhibit diminished motivation to invest in long-term land improvement or optimize resource utilization. This disincentive can lead to reduced adoption of modern cultivation practices and insufficient attention to proper land stewardship, ultimately exerting an adverse effect on technical efficiency. Seed procurement from personal or informal local sources often results in the use of low-quality seeds that are more susceptible to pests and diseases. Such suboptimal genetic material typically yields lower productivity and compromises crop resilience, thereby contributing to diminished output and reduced technical efficiency. Possession of non-farm income sources may divert farmers' focus away from agricultural activities, potentially reducing their commitment to farming operations and limiting investment in agronomic improvements. Farmers with supplementary income streams may, due to reduced reliance on agricultural earnings, demonstrate lower motivation to optimize production processes or adopt innovative farming techniques. This diminished engagement can consequently lead to suboptimal resource allocation and a decline in technical efficiency within wheat production systems.

Table 12- Factors affecting the technical efficiency of farmers producing rainfed wheat in Ahar County

Feature	Coefficient	Odds ratio	Feature	Coefficient	Odds ratio
herb	**1.074**	**2.927**	**Harvest_method_combinatorial**	**0.156**	**1.169**
Weed_control	0.895	2.448	Experience	0.142	1.153
Manure	0.827	2.286	Fam_mem_edu	0.096	1.101
Rental_value	0.505	1.658	Seed_purchase_score_jahad	0.088	1.092
Nitro	0.440	1.554	Residence_village	0.034	1.035
Farm_plots	0.380	1.462	Ownership_both	-0.251	0.777
Pest	0.263	1.301	Seed_purchase_source_self_farm	-0.306	0.736
Age	0.162	1.176	Nonfarm_income	-0.856	0.424

Fig. 8 presents a ranking of the relative influence exerted by each explanatory variable within the logistic regression model developed to analyze the technical efficiency of rain-fed wheat producers. The horizontal axis represents the magnitude and direction of the estimated coefficients, with positive values indicating factors that enhance efficiency, and negative values denoting those that diminish it. The vertical axis enumerates the various determinants of farmer efficiency. The length of each bar extending horizontally from the central axis reflects the strength of a given variable's impact on technical efficiency: longer bars to the right signify stronger positive influences, whereas longer bars to the left indicate more pronounced negative effects. As illustrated in the figure, herbicide application demonstrates the strongest positive effect on technical efficiency, while rural residence exhibits the weakest positive influence among the favorable factors. Conversely, mixed land ownership status (combining personal and rental plots) exerts the most substantial negative impact, whereas the presence of non-farm income sources displays the least detrimental, though still negative effect on technical efficiency.

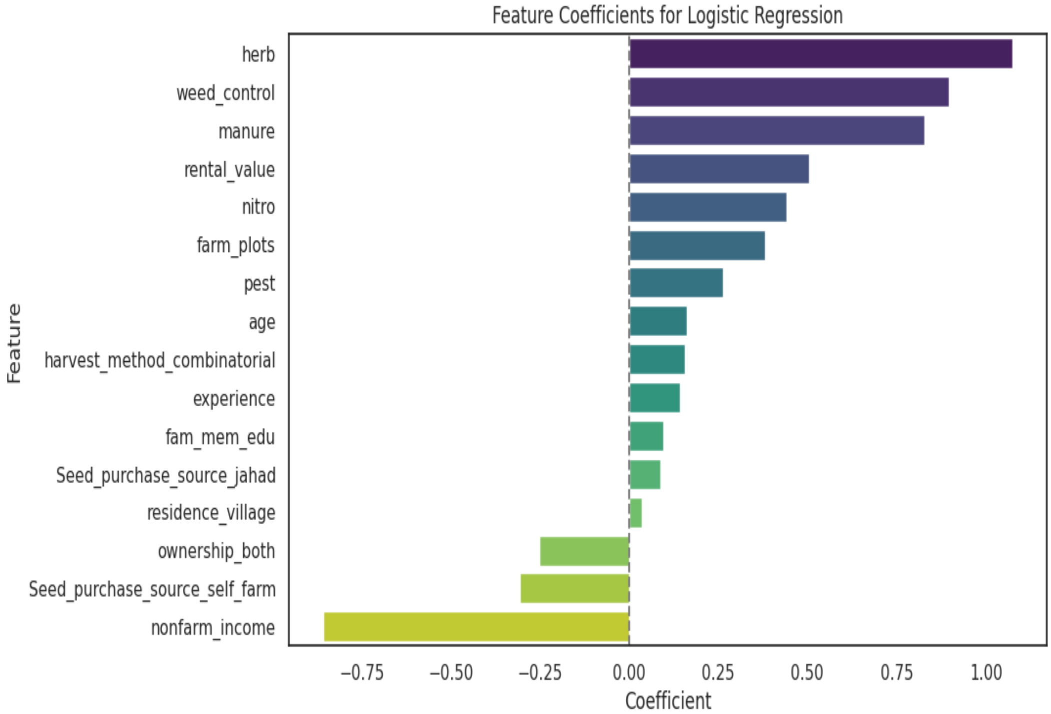

Figure 8- Examining the importance of variables that affect farmers' technical efficiency

Conclusion

This study was conducted with the objective of applying data mining techniques to analyze factors influencing the classification of rain-fed wheat producers in Ahar County based on their technical efficiency. The principal innovation of this research lay in the implementation and comparison of various machine learning algorithms to address an agricultural economics problem. The study demonstrated that integrating Data Envelopment Analysis (DEA) with machine learning algorithms can provide a powerful analytical framework for efficiency-related issues in the agricultural sector.

Subsequently, to predict farmers' efficiency and analyze its determinants, statistical methods were first employed to identify variables exhibiting significant associations with the target variable. Following the identification of these variables, machine learning algorithms, including Logistic Regression, Support Vector Machine, K-Nearest Neighbors, and Random Forest, were utilized to predict farmers' technical efficiency. Comparison of these algorithms through various performance evaluation metrics revealed that each method possesses distinct strengths and limitations in analyzing agricultural data. Model estimation and examination of results derived from the confusion matrix, accuracy, and error evaluation metrics, and ROC curves indicated that the Logistic Regression algorithm demonstrates superior predictive capability for farmers' efficiency compared to the other algorithms. This advantage primarily stems from its simpler structure, higher interpretability, and favorable performance with datasets of limited sample size.

Results obtained from the Logistic Regression algorithm indicated that the technical efficiency of rain-fed wheat producers in Ahar County is influenced by two principal groups of factors: those exerting positive effects and those exerting negative effects. Variables with positive impacts include herbicide application, weed control practices, manure usage, rental value of wheat cropland, nitrate fertilizer application, number of farm plots, pesticide use, farmer age, combined harvesting method, farming experience, presence of household members with university education, seed procurement from the Agricultural Jihad Organization, and rural residence. The second group comprises variables with negative effects, namely mixed ownership status of cropland (personal-rental combination), seed procurement from personal sources, and possession of non-farm income.

Findings showed that both positive and negative influences of various factors on the technical efficiency of rain-fed wheat producers in Ahar County, and given the efficacy of data mining techniques in identifying these determinants, several comprehensive and actionable management recommendations can be proposed. In particular, the optimal application of herbicides, pesticides, and appropriate fertilizers such as manure and nitrate fertilizer can significantly enhance farmers' technical efficiency. This finding is consistent with the results reported by Aryan *et al*. (2024). Therefore, it is recommended that educational and extension programs be implemented for farmers to enhance their knowledge and promote the optimal utilization of these agricultural inputs. In this context, data mining-based decision support systems can further assist farmers in selecting the optimal input combinations. The obtained results are consistent with the findings of Tanursaz *et al*. (2021) and Ghasemi *et al*. (2023). Additionally, emphasis should be placed on procuring seeds from certified and reputable sources, such as the Agricultural Jihad Organization, to improve sowing quality and ultimately enhance the productivity of rain-fed wheat farms. This finding also aligns with the results reported by Samson *et al*. (2024). On the other hand, factors such as mixed land tenure arrangements (combining personal ownership with rental plots) and the procurement of seeds from informal personal sources may place farmers in the lower efficiency frontier. Policymakers are therefore advised to enhance these farmers' motivation to improve technical efficiency through financial incentives, such as input and equipment purchase discounts targeted specifically at cultivators operating on leased agricultural farms. Enhancing access to certified seeds through the establishment of seed distribution centers in rural areas presents a viable opportunity for farmers to conveniently procure high-quality seeds at reasonable prices. Furthermore, fostering effective collaborations with seed-producing companies can guarantee both the quality and continuous supply of these seeds, ultimately contributing to enhanced agricultural productivity. In conclusion, this study clearly demonstrates that data mining approaches can serve as a powerful analytical tool in agricultural policymaking. By generating profound insights from existing datasets, such approaches can significantly improve decision-making processes across various managerial levels. For future research, it is recommended to employ more sophisticated deep learning algorithms as well as clustering techniques to enable a more precise analysis of efficiency patterns.

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مقاله پژوهشی

جلد ۴۰، شماره ۲، تابستان ۱۴۰۵، ص. ۱۲۷-۱۰۳

کاربرد داده‌کاوی در تحلیل عوامل مؤثر بر طبقه‌بندی کارایی فنی گندم‌کاران: مطالعه‌ای در شهرستان اهر

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تاریخ دریافت: ۱۴۰۴/۰۲/۱۳
تاریخ پذیرش: ۱۴۰۴/۰۹/۱۱

چکیده

شهرستان اهر به‌عنوان یکی از مناطق اصلی تولید محصولات کشاورزی، بخش قابل‌توجهی از گندم دیم استان آذربایجان شرقی را تولید می‌کند. بهبود کارایی فنی در این منطقه می‌تواند تأثیر قابل‌توجهی بر بهره‌وری و پایداری اقتصادی کشاورزان داشته باشد. بنابراین مطالعه حاضر با هدف کاربرد داده‌کاوی در تحلیل کارایی کشاورزان گندم دیم در شهرستان اهر انجام شد. بدین منظور کارایی فنی کشاورزان با استفاده از روش تحلیل پوششی داده‌ها محاسبه گردید و کشاورزانی که کارایی بالاتر از میانگین منطقه (یعنی ۰/۵۹) داشتند، به‌عنوان گروه کشاورزان با کارایی بالاتر از میانگین و بقیه به‌عنوان گروه کشاورزان با کارایی پایین‌تر از میانگین طبقه‌بندی شدند. سپس، با استفاده از آزمون‌های تی و خی‌دو، متغیرهایی که احتمال می‌رفت بر کارایی اثرگذار باشند، شناسایی شدند و برای طبقه‌بندی و تحلیل کارایی فنی از الگوریتم‌های یادگیری ماشین شامل رگرسیون لجستیک، ماشین بردار پشتیبان، k نزدیک‌ترین همسایه و جنگل تصادفی استفاده گردید. نتایج نشان داد که رگرسیون لجستیک عملکرد بهتری نسبت به سایر الگوریتم‌ها دارد. خروجی این الگوریتم حاکی از آن بود که عواملی مانند علف‌کش، کنترل علف‌های هرز، کود حیوانی، ارزش اجاره‌ای زمین‌ها، کود نیتراته، تعداد قطعه زمین‌ها، آفت‌کش، سن کشاورز، روش برداشت ترکیبی، تجربه، اعضای خانوار با تحصیلات دانشگاهی، تأمین بذر از جهاد کشاورزی و سکونت در روستا دارای تأثیر مثبت بر کارایی فنی می‌باشند. عواملی مانند، مالکیت زمین‌ها به‌صورت شخصی-اجاره‌ای، تأمین بذر از منابع شخصی و درآمد غیرکشاورزی نیز تأثیر منفی بر کارایی دارند. بر اساس نتایج، توصیه می‌شود کشاورزان آموزش‌های لازم در خصوص مدیریت بهینه مصرف نهاده‌های کشاورزی اثرگذار شامل علف‌کش، کود حیوانی، کود نیتراته و آفت‌کش را دریافت کنند. همچنین، سیاست‌گذاران با ارائه مشوق‌های مالی و خدمات مشاوره‌ای، انگیزه بهبود کارایی را در کشاورزانی که روی زمین‌های اجاره‌ای فعالیت می‌کنند، افزایش دهند. توسعه برنامه‌های حمایتی برای تأمین بذر و نهاده‌های کشاورزی با کیفیت از طریق جهاد کشاورزی نیز پیشنهاد می‌شود.

واژه‌های کلیدی: داده‌کاوی، کارایی فنی، گندم، یادگیری ماشین

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https://doi.org/10.22067/jead.2025.93203.1349

Journal of Agricultural Economics & Development

Homepage: https://jead.um.ac.ir

Research Article
Vol. 40, No. 2, Summer 2026, p. 129-150

Studying the Consequences of Adopting Smart Agricultural Technologies with the Moderating Role of Government Policies and Regulations

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Received: 17 July 2025 Revised: 17 February 2026 Accepted: 19 April 2026 Available Online: 19 April 2026	**How to cite this article:** Norouzi, H., Mola Ghalghachi, M., & Asgarnezhad Nouri, B. (2026). Studying the consequences of adopting smart agricultural technologies with the moderating role of government policies and regulations. *Journal of Agricultural Economics & Development, 40*(2), 129-150. https://doi.org/10.22067/jead.2026.94497.1364

Abstract

The agricultural sector is one of the areas where smart agricultural technologies are widely used. Smart farming technologies offer the potential to analyze agricultural data on a scale not previously possible. Adoption of smart farming technologies has the potential to improve productivity and profitability in agriculture, while also improving sustainability. Achieving this potential requires not only technological advancements, but also a thorough understanding of the consequences that the adoption of smart agricultural technologies should have. The aim of the present study is to study the consequences of adopting smart agricultural technologies with the moderating role of government policies and regulations. The statistical population of the research includes managers, experts, and specialists in the field of smart agriculture in Tehran and Alborz provinces, Iran. One of the methods for determining the minimum sample size is the ratio of the number of sample members to the number of questions in the research model or the N:q theory. Accordingly, considering the number of questionnaire items (27 questions), the sample size was estimated to be 270 people. The data collection tool is a questionnaire. The validity of the questionnaire was assessed in diagnostic, convergent and divergent terms, and the reliability of the questionnaire was also assessed using Cronbach's alpha coefficient and composite reliability. The research model was tested using the partial least squares method and Smart-PLS 3 software. The results of data analysis showed that the adoption of smart agricultural technologies has a positive and significant impact on workforce, economic, and environmental outcomes. Furthermore, government policies and regulations play a positive moderating role in the relationship between the adoption of smart agricultural technologies and workforce, economic, and environmental outcomes.

Keywords: Economic consequences, Environmental consequences, Smart farming, Technology adoption, Workforce consequences

https://doi.org/10.22067/jead.2026.94497.1364

Introduction

Agriculture, as the cornerstone of human civilization and economy, plays a vital role in providing livelihoods for communities (Azadi *et al.*, 2021). However, traditional production methods today grapple with serious challenges such as climate change, water scarcity, and heavy reliance on energy (Mana *et al.*, 2024). In this context, traditional agriculture brings devastating climatic consequences through the widespread emission of greenhouse gases, including carbon dioxide, nitrous oxide, and methane (Lieder & Schröter-Schlaack, 2021). Moreover, the use of chemical fertilizers and pesticides has led to soil and water pollution, and by generating nutrient runoff and releasing pollutants such as ammonia, it endangers human health and ecosystems (Ma *et al*., 2021). Furthermore, land-use changes, such as deforestation and land drainage, not only exacerbate greenhouse gas emissions but also pose a direct threat to biodiversity. The continuation of this situation could pose a serious crisis for food security and public health by reducing biodiversity and degrading foundational resources. Consequently, transitioning from traditional to modern agriculture is an undeniable necessity to meet the needs of a growing population. This transformation, known as the "Fourth Agricultural Revolution," leverages advanced technologies to establish a link between economic productivity and environmental sustainability, thereby ensuring future food security (Lieder & Schröter-Schlaack, 2021; Sambas *et al.*, 2023).

Researchers have defined this process of digital transformation in agriculture in various ways, such as "digital agriculture", "Agriculture 4.0" or "precision agriculture" (Mana *et al.*, 2024). In fact, the digital agriculture industry is experiencing a dynamic period of development in terms of technology supply. This newer phase has been termed the "digitalization" stage, and it is expected to have a greater impact on social and institutional spheres that require, and are increasingly dependent on, digital technologies (Giua *et al.*, 2022). The latest technological evolution has defined agriculture as "smart agriculture"—a "cyber-physical system"—in which intelligent technologies are considered the core control components of the farm (Mana *et al.*, 2024). The concept of smart agriculture can be applied to the notion of a "Smart Planet" (Li *et al.*, 2023), which is defined by various technologies such as "Internet of Things Technology (IoT)", "remote sensing technology", "big data analytics technology", "robotics and automation", "cloud and edge computing" and "artificial intelligence". By leveraging sensors, analytical software, and internet connectivity, these technologies enable data analysis and processing, timely decision-making, and precise monitoring in the field of agriculture (Otieno, 2023; Khaspuria *et al.*, 2024). Therefore, the adoption of smart farming technologies is not merely about using technological tools; their key role in data collection and analysis is of fundamental importance (Putri & Zainuddin, 2024).

The adoption of smart farming technologies can alleviate operational challenges in agriculture, including reducing stress, workload, and the time required for farmers' activities (Balafoutis *et al.*, 2020). By adopting these technologies, farmers will be able to overcome various obstacles and improve their overall well-being (Basir *et al.*, 2024). The primary goal of this modern approach is to increase crop production, minimize resource waste, and enhance profitability (Mutlaq *et al.*, 2022). The positive environmental consequences resulting from the adoption of smart farming technologies include optimizing irrigation, planting resilient varieties, employing soil and water conservation techniques, intelligently relying on data and climate forecasts, utilizing fertilizers correctly, and applying pesticides effectively and efficiently (De Pinto *et al.*, 2020; Fiawoo *et al.*, 2024). Consequently, smart agriculture has strong potential to increase agricultural productivity while maintaining sustainability and environmental compatibility (Navarro *et* *al.*, 2020). This is achieved by reducing the consumption of resources such as water and energy, as well as by minimizing negative environmental impacts (Virk *et al.*, 2020).

Considering the first aspect of the novelty of the present study, it can be stated that in previous research the consequences (outcomes) of adopting smart agricultural technologies have been examined less frequently, while most studies have focused on the factors (drivers or antecedents) and barriers to the adoption of smart agricultural technologies. For example, Dibern and his colleagues examined the main drivers and barriers to the adoption of digital agricultural technologies in their study (Dibbern *et al.*, 2024). The aim of the study by Khaspuria *et al.* (2024) was to conduct a comprehensive examination of the adoption of precision agriculture technologies among farmers. The aim of the study by Nandini and Venkataramana, (2024) was to investigate the limitations of adopting smart agricultural technologies. In addition, Mbanasor *et al.* (2024) examined the smart agricultural practices adopted by farmers. The main objective of the study by Shani *et al.* (2024) was to identify the determinants of the adoption of smart agricultural technologies. Bahari *et al.* (2024) aimed to examine the factors influencing the adoption of Internet of Things (IoT) technology in smart agriculture. The objective of the study by Li *et al.* (2023) was to investigate the behavioral adoption mechanism of smart agricultural technologies. The main objective of the study by Serote *et al.* (2023) was to examine the barriers to the adoption of smart irrigation technologies for sustainable crop productivity. In addition, Mhlanga and Ndhlovu, (2023) sought to examine the challenges and complexities associated with the adoption of digital technologies in the agricultural sector. On the other hand, regarding the second aspect of the study's novelty, it can be stated that a review of the theoretical literature indicates that previous studies have rarely examined the effect of adopting smart agricultural technologies on workforce, economic, and environmental outcomes with the moderating role of government policies and regulations. Instead, most studies have mainly focused on the relationship between the adoption of smart agricultural technologies and workforce, economic, and environmental outcomes; For example, Fiawoo and colleagues sought to examine the adoption of smart agricultural technologies and their impact on farmers' performance and income (Fiawoo *et al.*, 2024). Jabbari and colleagues, in their study, examined the effect of farmers' perceptions and adoption of smart technologies on crop health and yield prediction (Jabbari *et al.*, 2023). Nansky and colleagues, in their study, aimed to examine the impact of smart agricultural technologies on rice production in Japan (Nanseki *et al.*, 2023). Yamowa and Kaba, in their study, sought to examine the impact of integrating smart agricultural technology adoption skills and agricultural business management skills on improving the livelihoods of women farmers (Yamoah & Kaba, 2024). Finally, the aim of the study by Zolfaghar and colleagues was to examine the relationship between the use of smart agricultural technologies and the improvement of resource productivity (Zulfikhar *et al.*, 2024).

The adoption of smart agricultural technologies is essential for transforming traditional farming practices, overcoming the various changes and transformations in modern agriculture, and paving the way for a more sustainable and efficient future in the agricultural sector. In the present study, the consequences of adopting smart agriculture technologies are examined with the moderating role of government policies and regulations among managers, specialists, and experts in the field of smart agriculture in Tehran and Alborz provinces. Given the above explanations, the main research question can be formulated as follows: Does the adoption of smart agriculture technologies have a significant effect on workforce, economic, and environmental outcomes, with government policies and regulations playing a moderating role? Conducting the present study in the field of smart agriculture in Tehran and Alborz provinces can facilitate farmers' livelihoods, accelerate the country's economic growth, and consequently lead to a reduction in environmental impacts. On the other hand, providing appropriate programs, considering financial incentives, and avoiding the implementation of overly strict policies by the government play an effective role in the adoption of smart agricultural technologies and their resulting outcomes.

Background

Smart agriculture and digital agriculture have emerged as modern strategies aimed at transforming agriculture into a sustainable and productive industry (Otieno, 2023). Smart agriculture, through a precise approach based on the efficient utilization of resources—aligned with environmental considerations—can support sustainable agriculture. In this framework, smart agriculture typically refers to a set of electronic platforms, hardware, and software utilized for collecting, transmitting, and leveraging farm data. These data can include information regarding soil nutrient status, moisture, atmospheric conditions, and other indicators related to the cultivation environment, and can be connected to the system through technological devices such as mobile phones, tablets, and sensor systems. In other words, smart agriculture relies on the synergy between hardware and software layers, linking data and decision-making tools to optimize processes, ensure efficient resource use, increase agricultural land productivity, and improve water consumption management (Putri & Zainuddin, 2024). In other definitions, digital agriculture is described as an agricultural management system that utilizes modern technologies to achieve optimal production in accordance with resource constraints (Hashim *et al.*, 2024; Alumfareh *et al.*, 2024; Von Guionneau, 2024). Also, digital agriculture can be considered the result of integrating various smart technologies that provide the basis for informed decision-making as well as process automation in the field of agriculture (Mutlaq *et al.*, 2022). Ultimately, this approach also creates the capacity to carry out automated operations with minimal human intervention (Hashim *et al.*, 2024). Accordingly, some of the key and prominent technologies in the field of smart agriculture are introduced (Otieno, 2023). These technologies include (Kernecker *et al.*, 2020; Balafoutis *et al.*, 2020; Otieno, 2023):

IoT

This technology forms the backbone of smart farming. By connecting physical devices and sensors to the internet, it enables accurate data collection and remote monitoring (Balafoutis *et al.*, 2020; Hussien *et al.*, 2023). In fact, it collects real-time data on soil moisture, temperature, plant growth, crop health, and other environmental factors, so that farmers can make better data-driven decisions and optimize resource allocation (Otieno, 2023).

Remote Sensing Technology

Remote sensing technologies, such as unmanned aerial vehicles (drones), provide valuable insights into agricultural fields and their crops (Otieno, 2023). A drone, after receiving the initial information, flies along the optimal path and begins performing its tasks such as irrigation, spraying, or even collecting data and capturing images of the agricultural field (Balafoutis *et al.*, 2020; Otieno, 2023). In addition, other technologies such as hyperspectral imaging and multispectral cameras collect high- resolution images and multispectral data (Otieno, 2023).

Big Data Analytics Technology

The ability to process and analyze large volumes of data is crucial in smart agriculture (Balafoutis *et al.*, 2020). These technologies are used to analyze big data related to weather, soil, and historical crop records (Otieno, 2023). By analyzing these data, farmers can enhance their crop performance (Otieno, 2023).

Robotics and Automation

Autonomous robots and drones equipped with sensors and cameras can perform tasks such as seeding, spraying, and harvesting with high precision and efficiency (Aslan *et al.*, 2022). The deployment of robots in agricultural fields can identify weeds, pests, and nutrient deficiency spots, and subsequently monitor yield, crop quality, and other applications (Otieno, 2023; Mesías-Ruiz *et al.*, 2023). It is noteworthy that the robotic tractor is one of the best‐known robots, capable of operating automatically or without a human operator to perform tillage (Nanseki & Chomei, 2023).

Cloud Computing and Edge Computing

Cloud computing enables the storage, processing, and analysis of agricultural data on remote servers, facilitating scalability and accessibility (Emmi *et al.*, 2023). On the other hand, edge computing brings computational capabilities closer to the devices that generate the data and to the farmers who need it, thereby accelerating real-time decision-making at the field level. Therefore, cloud computing and edge computing support the integration of data from various sources and enable efficient data analysis (Otieno, 2023).

Artificial Intelligence

AI can assist farmers from soil preparation for planting to harvesting through robots and computer engines. In other words, artificial intelligence has considerable potential to enhance the sustainability of the agricultural industry through various applications. For example, it can help identify the optimal timing for harvesting fruits and vegetables, reduce waste, and monitor the health of soil and crops (Mana *et al.*, 2024).

It is important to note that the aforementioned technologies are continuously evolving and becoming more sophisticated. As these technologies continue to advance, farmers can use them to improve productivity, conserve resources, minimize environmental impacts, and contribute to global food security in a rapidly changing and evolving world (Otieno, 2023).

In connection with the expansion of the research hypotheses, it can be argued that the implementation of smart technologies in agriculture is vital to support the advancement of this sector (Nugroho & Aliwarga, 2019). Balafoutis *et al.* (2020)believe that the adoption of smart farming technologies can facilitate agricultural practices, such as farmer stress, farmer workload, and working hours, in addition to work-related injuries. It should be noted that even if it is shown that farmers' stress is significantly reduced, the actual use of a smart agricultural technology can still cause considerable stress due to the need for information processing and technology calibration, as well as when the technologies fail. Of course, stress levels vary across different types of smart farming technologies. Guidance technologies, which have been efficient for years, reduce stress more than variable rate technologies (VRT) that require precise and continuous calibration for proper performance compared to conventional uniform applications. Moreover, the adoption of smart farming technologies reduces farmers' workload and makes life easier for them (Balafoutis *et al.*, 2020). If implemented using modern and efficient technologies, smart farming can make the cultivation process more effective, increase production, and ultimately improve farmers' well-being. In other words, by adopting smart farming technologies, farmers can overcome various challenges in agriculture and improve their overall well-being (Basir *et al.*, 2024). Furthermore, the digitalization of agriculture makes production-related tasks possible at lower cost and in a shorter time, and it transforms farmers' performance (Munnisunker *et al.*, 2022; Javaid *et al.*, 2023).

The digitalization of activities and relationships can introduce new risks to occupational health and safety, such as increased mental workload and the blurring of personal and professional boundaries. While these significant technical advancements may lead individuals—particularly the elderly—to doubt their knowledge and even place them in situations where they feel incapable, resulting in substantial personal instability, learning new technologies or methods through training can be challenging (Munnisunker *et al.*, 2022; Javaid *et al.*, 2023). Good change management involves anticipating psychological risks (such as feelings of dependence, loss of autonomy and identity, and additional mental workload) as well as physical risks resulting from robot malfunction. This approach allows the project to be implemented without causing significant disruption to work settings, tasks, or responsibilities (Mana *et al*., 2024). Therefore, although the adoption of smart farming technologies in agriculture may create new concerns regarding occupational or work-related risks, it can protect farmers from the effects of changes in the workforce force (Munnisunker *et al*., 2022; Javaid *et al*., 2023).

The findings of Yamoah and Kaba, (2024) indicate that social outcomes are among the key consequences of adopting smart farming technologies. The results of Nanseki (2022) study indicated the positive impact of smart farming technologies on workforce savings. Mamilianti (2020) research confirmed that the use of technology can shape positive farmer behavior; therefore, in line with the literature, the first research hypothesis is proposed.

$\boldsymbol{H_1}$: The adoption of smart farming technologies has an effect on workforce -related outcomes.

Smart farming technologies become prominent when it is believed that their economic benefits for farmers are significant. The use of smart farming technologies increases productivity, income, and energy optimization (Balafoutis *et al*., 2020). Other economic aspects of smart farming technology adoption include the reduction of input costs such as seeds, fertilizers, pesticides, energy, and irrigation, as well as the decrease in variable costs such as raw materials, packaging, and workforce (Madushanki *et al*., 2019). Furthermore, improved product quality, such as being healthy, clean, pest-free, fresh in appearance, with natural and sufficient physiological and morphological growth, ripeness, firmness, free from spoilage affecting edibility, and the absence of defects, are other key outcomes of adopting smart farming technologies (Balafoutis *et al*., 2020). Smart farming not only provides numerous economic benefits for farmers, but also contributes to the growth of a country's economy (gross domestic product) (Otitoju *et al*., 2023). The application of Internet of Things technology in the agricultural sector has numerous advantages. It allows producers (farmers) to increase their productivity and produce more by saving resources (e.g., water) (easy resource management) (Ragaveena *et al*., 2021; Cihan, 2023). It enables the rapid detection of crop diseases or pests and the implementation of necessary actions (Javaid *et al*., 2023). In general, Internet of Things technology allows farmers to make better decisions through precise data analysis (Cihan, 2023).

Kasimati *et al*. (2024) in their study, concluded that the adoption of smart farming technologies is effective in improving product quality and increasing economic growth. The results of the study by Yamoah and Kaba, (2024) indicate that economic outcomes are one of the key consequences of adopting smart farming technologies. The results of the study by Nanseki and Chomei, (2023) showed that smart farming technologies have a significant impact on economic performance. The results of the study by Pal *et al*. (2022) confirmed that smart farming technologies can create positive economic outcomes; therefore, based on the explanations provided, the second research hypothesis is stated.

$\boldsymbol{H_2}$ **:** The adoption of smart farming technologies has a positive and significant effect on economic outcomes.

There is now a clear understanding of how smart farming technologies can provide a solution to environmental problems by reducing human intervention through automation (Ena & Huib, 2023). Smart farming technologies can help farmers produce crops more efficiently (Kernecker *et al*., 2020) and protect the environment and natural resources (Paul *et al*., 2021). The reduction in the use of fertilizers, pesticides, irrigation water, and greenhouse gas emissions is associated with the environmental outcomes of adopting smart farming technologies (Balafoutis *et al*., 2020). By using these technologies, natural resources such as water, soil, and energy can be utilized more efficiently, their consumption can be reduced, and farmers can also be enabled to operate in an environmentally compatible manner (Cihan, 2023). Smart farming technologies, such as Internet of Things (IoT)-based technologies, provide promising solutions for the precise management of resources (Zulfikhar et al., 2024). Internet of Things (IoT) technology can be applied in various areas of agriculture, such as soil management, crop growth, water management, product tracking, and supply chain management. IoT-based sensors enable real-time monitoring of soil moisture levels (Singh *et al.*, 2023) and enhance the overall efficiency of water use in agriculture (Zulfikhar *et al.*, 2024). By employing this technology, crop producers can improve the health and quality of their products and provide consumers with healthier food products. Overall, Internet of Things (IoT) technology offers numerous benefits in the agricultural sector, such as improving productivity, enabling the sustainable use of natural resources, and enhancing product quality (Cihan, 2023). Furthermore, precision agriculture technologies contribute to the efficient use of nutrients and crop management, potentially reducing the environmental footprint of agricultural activities (Singh *et al.*, 2023). The integration of precision agriculture technologies leads to a significant reduction in water consumption while simultaneously increasing crop yield (Zulfikhar *et al.*, 2024). By using these technologies, farmers can make informed decisions regarding pest control, irrigation, and fertilization, which leads to increased efficiency, reduced waste, and higher crop yields (Pal & Joshi, 2023). On the other hand, Loures *et al.* (2020) examined the impact of using remote sensing techniques on small farms. They concluded that the efficient use of these technologies improves crop productivity and farm profitability, and promotes sustainable agriculture both ecologically and economically (Otieno, 2023). Overall, the use of smart farming technologies can help address critical concerns such as water scarcity, energy consumption, and land use, leading to more sustainable agricultural practices (Pal & Joshi, 2023). In other words, smart farming enables farmers to achieve better performance by optimizing farm management, reducing the use of fertilizers, pesticides, and water, and contributing to improved and more sustainable outcomes (Otieno, 2023).

The adoption of smart farming technologies can lead to a reduction in greenhouse gas emissions (nitrous oxide, methane, and carbon dioxide), thereby positively influencing climate change mitigation and reducing global warming potential. It can contribute to biodiversity by optimizing inputs (such as variable-rate fertilization or pesticide application) and reducing spray drift (Balafoutis *et al.*, 2020). In addition, the adoption of these technologies can reduce the impacts of weed, pest, and disease growth on farmland and crops (Balafoutis *et al.*, 2020; Lieder & Schröter-Schlaack, 2021). Moreover, the use of small-scale robots for planting can prevent environmental damage caused by heavy machinery and help preserve soil sustainability (Lieder & Schröter-Schlaack, 2021). It is noteworthy that the findings of Yamoah and Kaba, (2024) indicate that environmental outcomes are among the key consequences of adopting smart farming technologies. Furthermore, the study by Kasimati *et al.* (2024) revealed that the adoption of smart farming technologies is effective in reducing environmental impacts; therefore, based on the explanations provided, the third research hypothesis is formulated.

H_3: The adoption of smart farming technologies has a positive and significant effect on environmental outcomes.

Government support plays an important role in facilitating the adoption of smart farming technologies (Bahari *et al.*, 2024). In other words, policies and initiatives that promote the use of smart farming technologies can have a positive impact on farmers' decisions to adopt these technologies (Sun *et al.*, 2021; Everest, 2021). Farmers' perception of active government support plays a significant role in their decision to adopt smart farming technologies (Jabbari *et al.*, 2023; Meng *et al.*, 2023). When farmers perceive that the government actively supports the adoption and implementation of smart technologies in agriculture, they are more likely to embrace these technologies. Government support can include financial incentives such as subsidies, policy frameworks, and support programs (Sun *et al.*, 2021; Everest, 2021; Singh *et al.*, 2021; Meng *et al.*, 2023). Government support creates a conducive environment for farmers, builds their trust, and reduces potential barriers to adoption. In this way, government support reflects its commitment to modernizing the agricultural sector and promoting sustainable farming practices (Meng *et al.*, 2023). Accordingly, the availability of accurate information and educational resources is important for the successful adoption of smart farming technologies. Farmers need precise and up-to-date information about smart farming technologies and their efficient implementation. Training programs and workshops can enhance farmers' understanding of these technologies (Sun *et al.*, 2021; Everest, 2021). Studies have shown that farmers who have access to comprehensive information and training programs are more likely to adopt smart technologies in their agricultural activities and use them effectively. Available information channels, such as agricultural extension services, workshops, seminars, and online resources, help farmers understand the benefits and outcomes of smart farming technologies (Haque *et al.*, 2021; Li *et al.*, 2023). Farmers must have access to training programs to acquire the skills and knowledge necessary for efficient and effective use of the technologies (Singh *et al.*, 2021). Therefore, reducing training costs and equipping farmers with essential skills through government-supported programs can significantly increase the use of smart farming technologies, thereby improving their effectiveness and efficiency (He *et al.*, 2023).

On the other hand, imposing taxes or levies on certain smart farming technologies significantly increases the cost of access to these technologies (Chen *et al.*, 2023). Although countries like China and the United States have the potential and capability to produce these technologies and benefit from cost reductions and competitive prices, some countries (mostly developing ones) import and then assemble these technologies, which leads to increased costs due to the payment of tariffs. To increase affordability and support domestic production, it is necessary to invest in the local manufacturing of smart farming technologies (Makam *et al.*, 2024) or to provide financial incentives such as subsidies, tax exemptions, and grants for importing these technologies (Jiang & Xu, 2023).

Islam *et al.* (2024) found in their study that the lack of government support, the implementation of strict policies, and the absence of appropriate government programs are among the barriers to the adoption of smart farming technologies. The results of the study by Jaroenwanit *et al.* (2023) indicate that government support had the greatest influence on smart agricultural decision-making in risk management. Azam and Shaheen, (2018) conducted a government-supported study in which they examined the factors influencing farmers' decision-making in smart farming. Their findings showed that marketing factors and government policies are the most important elements in persuading farmers to adopt smart farming practices, regardless of their level of education. In fact, the results of this study indicate that the adoption of smart farming is unlikely to be achieved without government support. Furthermore, the results of the study by Aryal *et al.* (2018) confirmed that government support is an important factor in the adoption of smart farming. Amondo and Simtowe, (2018) found that farmers who rejected smart farming technology discontinued its adoption and use for a period of time and eventually stopped using it altogether. This was mainly due to the lack of serious and continuous government promotion; therefore, based on the explanations provided, the fourth and fifth hypotheses and the research are presented.

$\boldsymbol{H_4}$**:** Government policies and regulations positively moderate the relationship between the adoption of smart farming technologies and workforce -related outcomes.

$\boldsymbol{H_5}$**:** Government policies and regulations positively moderate the relationship between the adoption of smart farming technologies and economic outcomes.

$\boldsymbol{H_6}$**:** Government policies and regulations positively moderate the relationship between the adoption of smart farming technologies and environmental outcomes.

Based on the explanations provided, the conceptual model of the study is presented in Fig. 1.

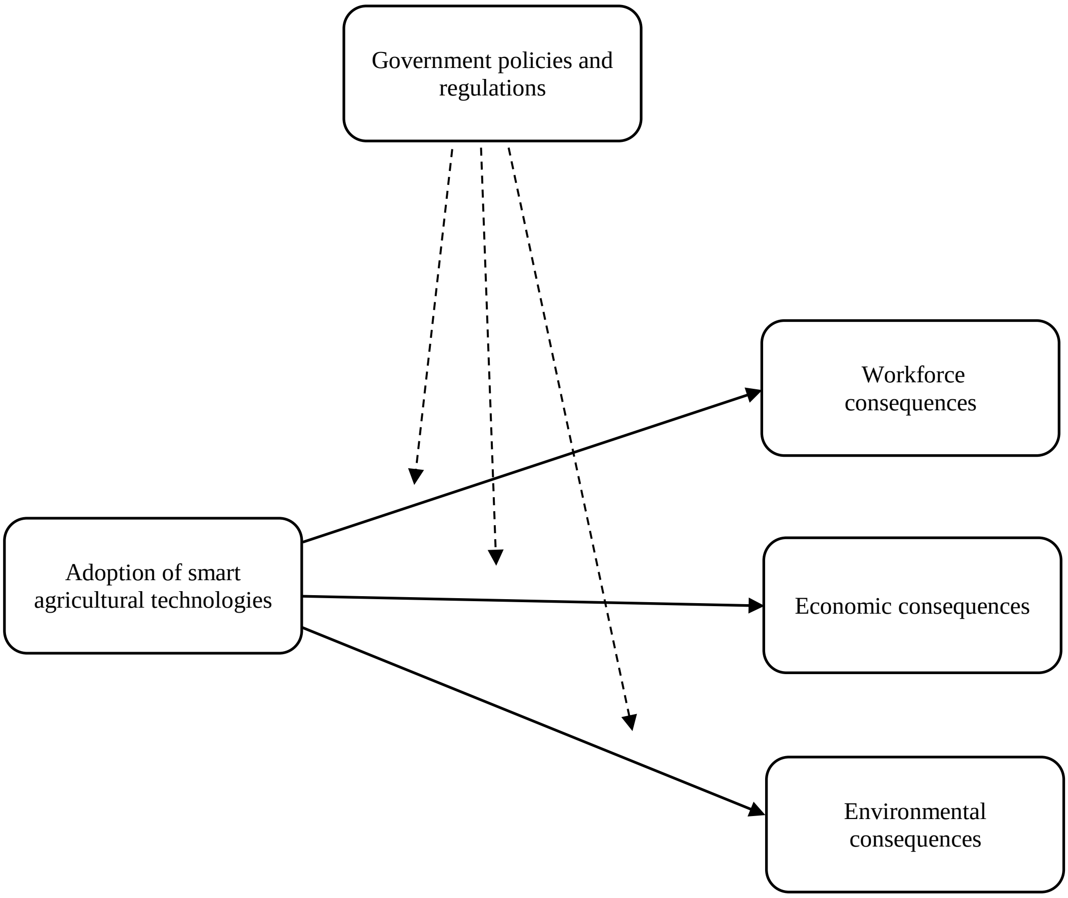

Figure 1- Conceptual model of the study

References (Islam *et al*., 2024; Zulfikhar *et al*., 2024; Basir *et al*., 2024; Bahari *et al*., 2024; Cihan, 2023; Jabbari *et al*., 2023; Lieder & Schröter-Schlaack, 2021; Balafoutis *et al*., 2020; Kernecker *et al*., 2020**)**

Methodology

Population and Sample of the Study

The target population of this study consists of managers, specialists, and experts in the field of smart agriculture in Tehran and Alborz provinces, Iran. This study is applied in terms of its purpose and descriptive‐survey in terms of its nature and methodology. The sampling method is non‐probability convenience sampling. One of the methods for determining the minimum sample size is the ratio of the number of sample members to the number of items in the research model, known as the N:q theory. The minimum recommended ratio proposed by Jackson (2003) is 10:1 (Norouzi *et al*., 2024). Accordingly, considering the number of questionnaire items (27 questions), the sample size was estimated to be 270 participants. However, to ensure adequacy, a larger sample—15 times the number of items, equivalent to 405 questionnaires—was distributed in person. Ultimately, 350 completed questionnaires were collected and analyzed.

Data Collection Instrument

In the present study, a questionnaire has been used as the data collection instrument. The instrument was designed and structured based on two sections: demographic data and specialized questions. The first section includes questions regarding the respondents' general characteristics, such as gender, marital status, age, education level, and work experience, while the information in the second section is presented in Table 1. Additionally, the scale used in the questionnaire is a five-point Likert scale consisting of: strongly disagree, disagree, neutral, agree, and strongly agree.

Table 1- Composition of the questionnaire's specialized questions

Row	Variables	Number of questions	References
1	Acceptance of Smart Agriculture Technologies	4	Hosseininia *et al*., 2021
2	Government Policies and Regulations	4	Bahari *et al*., 2024; Islam *et al*., 2024
3	workforce Force Consequences	6	
4	Economic Consequences	6	Balafoutis *et al*., 2020; Kernecker *et al*., 2020
5	Environmental Consequences	7	

Statistical Analysis Methods

The collected data were analyzed using structural equation modeling (SEM) with a partial least squares (PLS) approach, employing the Smart‐PLS 3 software. Since the partial least squares technique is less sensitive to sample size and does not require data normality, this software was selected.

Descriptive Analysis

Regarding the results of the respondents' demographic characteristics, which include managers, specialists, and experts in the field of agriculture, it can be explained that 21.6% of the respondents are female and 78.4% are male. A total of 27.2% of the respondents are single, and 72.8% are married. The largest proportion of respondents, equivalent to 45.2%, are between 41 and 50 years old, while the smallest proportion, about 9.6%, are between 20 and 30 years old. Regarding educational status, the largest proportion of respondents, equivalent to 55.2%, hold doctoral degrees, while the smallest proportion, about 1.2%, have a high‐school diploma or lower. Finally, the largest proportion of respondents, equivalent to 27.2%, have 6 to 10 years of work experience, while the smallest proportion, about 12.8%, have less than 5 years of work experience.

Inferential Analysis

For the statistical analysis, structural equation modeling was used, employing the measurement model followed by the structural model. The measurement model represents the manner in which latent and observed variables are related, while the structural model indicates the relationships between latent or underlying variables (Asgarnezhad Nouri *et al*., 2022). In the present study, several validity criteria—including construct validity, convergent validity, and discriminant validity—along with two reliability coefficients, namely composite reliability and Cronbach's alpha, were used to assess the fit of the measurement model. Asgarnezhad Nouri *et al.* (2022) believe that construct validity indicates the degree of consistency between the results obtained from applying the measurement instruments and the theories upon which the test is designed. In addition, discriminant validity is used to examine the extent to which the items of one factor differ from the items of other factors. Convergent validity is also employed to assess the degree of correlation between each factor and its own corresponding items (Reshadatnia *et al*., 2020).

Table 2– Results of construct validity (Confirmatory factor analysis) and reliability.

Variable	Item	Factor loading	Cronbach's Alpha	Composite reliability
Acceptance of smart agriculture technologies	1. I accept the use of smart agriculture technologies in the near future.	0.814	0.846	0.897
	2. I recommend the use of smart agriculture technologies to others.	0.825		
	3. I accept continuing the use of smart agriculture technologies.	0.849		

Government policies and regulations	4. I accept repeated use of smart agriculture technologies.	0.821	0.865	0.908
	5. Promoting smart agriculture requires sufficient government support, including providing adequate internet infrastructure in rural areas, launching training programs for technicians, educating farmers, offering easy loan facilities for start‑ ups and farmers, supplying auxiliary equipment, and other related support.	0.858		
	6. The government provides various forms of support to agricultural organizations to introduce smart agriculture technologies.	0.832		
	7. The government promotes smart agriculture by disseminating successful case studies and providing technical training.	0.842		
	8. The government supports various agricultural information projects for agricultural organizations.	0.842		
Workforce force consequences	9. Adoption of smart agriculture technologies can reduce work time through applications such as robotics, auto guidance, and remote operations.	0.597	0.876	0.908
	10. Adoption of smart agriculture technologies can reduce farmers' stress through better resource optimization and operational planning.	0.834		
	11. Adoption of smart agriculture technologies can decrease heavy workforce by using automation and robotic technologies for demanding field operations.	0.852		
	12. Adoption of smart agriculture technologies (equipment such as automation and robotics) can reduce farmers' injuries, for example, automatic coupling or automatic filling of sprayers.	0.804		
	13. Adoption of smart agriculture technologies can decrease occupational physical or psychological harm through providing advanced sensors for active and passive operations.	0.820		
Economic consequences	14. Adoption of smart agriculture technologies can provide better information for farmers' decision-making.	0.808	0.862	0.896
	15. Adoption of smart agriculture technologies can increase productivity (efficiency and effectiveness).	0.803		
	16. Adoption of smart agriculture technologies can improve product quality (e.g., healthiness, cleanliness, pest‑ free condition, fresh appearance, adequate physiological and morphological growth, ripeness, firmness, absence of decay affecting edibility, and lack of defects).	0.809		
	17. Adoption of smart agriculture technologies can reduce input costs (e.g., seed, fertilizer, pesticides, fuel, and irrigation) and variable costs (e.g., raw materials, packaging, and workforce).	0.777		
	18. Adoption of smart agriculture technologies can help increase income through optimizing production and product quality.	0.768		
	19. Adoption of smart agriculture technologies can contribute to better product preservation, selective harvesting, and reducing product loss or waste (e.g., fruits with spots, pest marks, or irregular shapes caused by abnormal growth).	0.731		
Environmental consequences	20. Adoption of smart agriculture technologies can reduce energy consumption and related costs (e.g., tractor use).	0.716	0.895	0.918
	21. Adoption of smart agriculture technology can lead to lower greenhouse gas emissions (nitrous oxide, methane, and carbon dioxide), positively influencing climate change and global warming potential.	0.854		
	22. Optimized crop production using smart agriculture technologies can preserve biodiversity and soil sustainability or contribute to maintaining soil health.	0.798		
	23. Adoption of smart agriculture technologies can support biodiversity by optimizing inputs (variable‑ rate fertilization or pesticide application) and reducing spray drift.	0.803		

24. Adoption of smart agriculture technologies can reduce pesticide use and fertilizer consumption in agricultural production.	0.816
25. Adoption of smart agriculture technologies can reduce pesticide residues.	0.797
26. Optimizing water use through the application of smart agriculture technologies helps conserve water resources and reduce excessive pumping.	0.743
27. Adoption of smart agriculture technologies can reduce the effects of weed growth, pests, and diseases in the field.	0.704

On the other hand, composite reliability and Cronbach's alpha coefficient indicate the internal consistency of the items that measure the same construct (Mola Ghalghachi & Bashir Khodaparasti, 2023).

Measurement Model

To evaluate the fit of the measurement model, two indices—reliability and validity—were used, as presented in Table 2.

The reliability of the research questionnaire was assessed using factor loadings (confirmatory factor analysis), Cronbach's alpha coefficient, and composite reliability. The desirable value for factor loadings, Cronbach's alpha, and composite reliability is preferably above 0.7 (Mola Ghalghachi & Bashir Khodaparasti, 2023). Therefore, the values presented in Table 2 indicate highly desirable factor loadings—namely, above 0.7 for each observed variable. Moreover, the results for Cronbach's alpha and composite reliability also demonstrate the satisfactory reliability of the variables.

On the other hand, the results of convergent and discriminant validity are presented in Table 3. It should be noted that in the present study, the Fornell–Larcker criterion was used to assess discriminant validity.

Table 3- Assessment of Convergent and Discriminant Validity of the Measurement Model

Variable	Average Variance Extracted (AVE)	Fornell–Larcker 1	2	3	4	5
1. Government Policies and Regulations	0.711	0.843				
2. Acceptance of Smart Agriculture Technologies	0.685	0.446	0.827			
3. Workforce Force Consequences	0.590	0.498	0.470	0.768		
4. Economic Consequences	0.615	0.623	0.623	0.709	0.784	
5. Environmental Consequences	0.625	0.545	0.513	0.579	0.730	0/790

Based on Table 3, the Average Variance Extracted (AVE) criterion was used to assess convergent validity. According to Mola Ghalghachi and Bashir Khodaparasti, (2023), this criterion reflects the extent to which a construct correlates with its own indicators, and they further note that the greater this correlation is, the better the model fit will be. Therefore, the point that "the desirable value for the Average Variance Extracted (AVE) criterion should be above 0.50" is satisfied in Table 3. Furthermore, Asgarnezhad Nouri *et al*. (2022) believe that the Fornell–Larcker criterion represents the extent to which a construct is more strongly related to its own indicators compared to its relationships with other constructs. The results are interpreted such that if the square root of the Average Variance Extracted (AVE) for the latent variables—shown in the cells along the main diagonal of the matrix—is greater than the correlation values in the cells below and to the right of the diagonal, then discriminant validity is considered satisfactory (Mola Ghalghachi & Bashir Khodaparasti, 2023). Therefore, Table 3 indicates that the variables exhibit acceptable discriminant validity. Structural model.

It is worth noting that the output of the conceptual model of the research can be presented in Fig. 2.

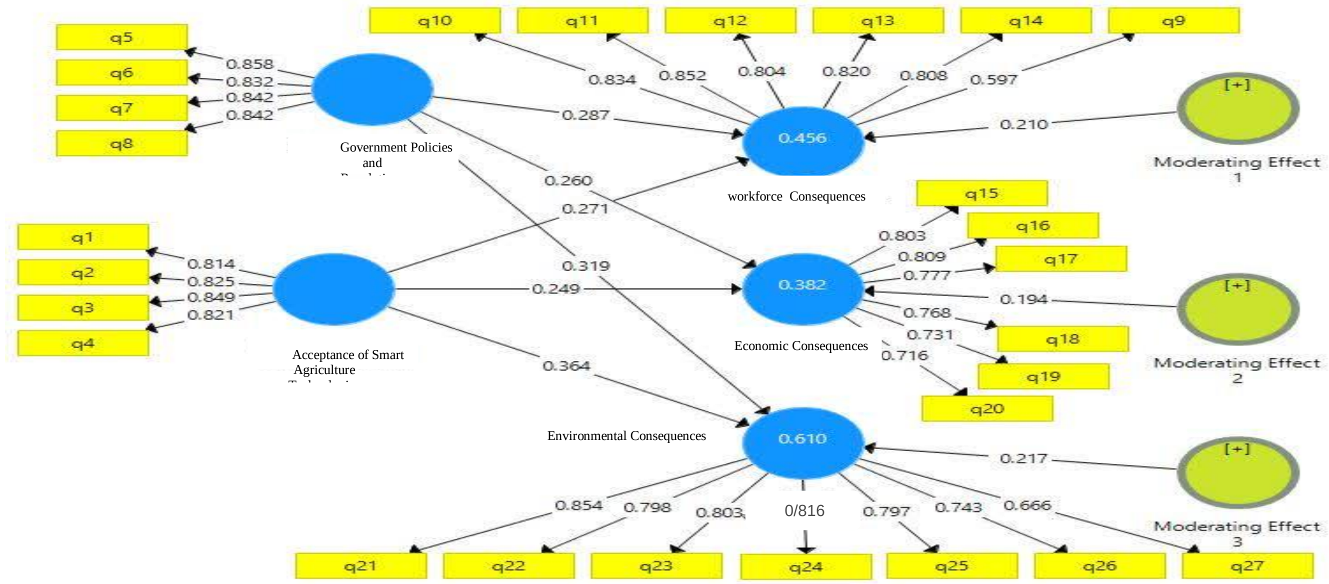

Figure 2- Model output including path coefficients, determination coefficients (R^2), and factor loadings

Regarding the analysis of Fig. 2, it can be stated that since the path coefficients, or beta coefficients, represent the amount of explanation, strength, and direction of the effect between two latent variables—and their values range between -1 and +1—there is a linear relationship between the latent variables of the study according to Fig. 2. In Fig. 2, the numbers between the observed and latent variables (confirmatory factor analysis) represent the factor loadings. Additionally, the numbers between the latent variables indicate the path coefficients, and the numbers inside the circles represent the determination coefficients (R^2) of the endogenous latent variables. On the other hand, Fig. 3 shows the research model output along with the t-values.

After obtaining the conceptual model output along with the path coefficients, the research model output including the significance of t-values is generated to examine the significance of the paths. The t-value significance numbers serve as a criterion for assessing the relationships between variables in the structural model. If these values exceed 1.96, the validity of the relationships between constructs—and consequently the confirmation of the research hypotheses—is supported at various confidence levels. Therefore, Fig. 3 indicates the confirmation of the model's paths.

It should be noted that, according to the software output, the results of the research hypotheses are explained in Table 4.

Based on Table 4, all hypotheses are supported because the path coefficients are positive and the t-values are greater than 1.96.

The values related to the model fit indices are presented in Table 5.

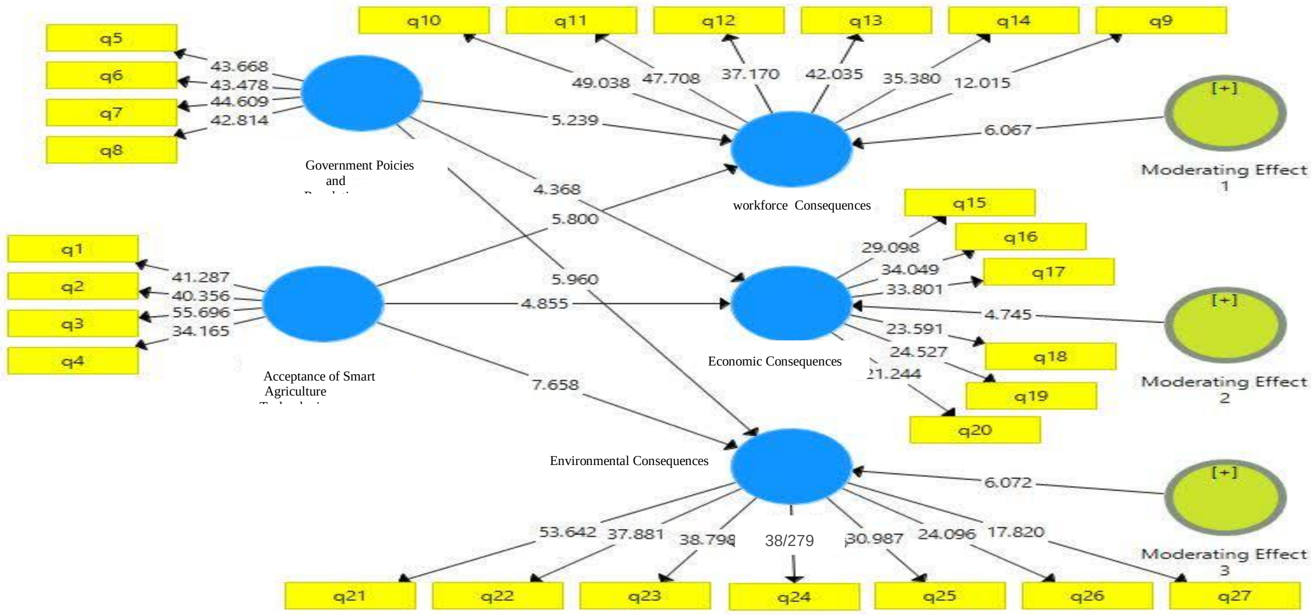

Figure 3- Model output including t-statistics significance coefficients

Table 4- Results of the hypotheses

Hypothesis	Path coefficient	t-value	Result
1. Acceptance of smart agriculture technologies affects workforce force Consequences.	0.271	5.800	Supported
2. Acceptance of smart agriculture technologies has a positive and significant effect on economic Consequences.	0.249	4.855	Supported
3. Acceptance of smart agriculture technologies has a positive and significant effect on environmental Consequences.	0.364	7.658	Supported
4. Government policies and regulations positively moderate the relationship between acceptance of smart agriculture technologies and workforce force Consequences.	0.287	5.239	Supported
5. Government policies and regulations positively moderate the relationship between acceptance of smart agriculture technologies and economic Consequences.	0.260	4.368	Supported
6. Government policies and regulations positively moderate the relationship between acceptance of smart agriculture technologies and environmental Consequences.	0.319	5.960	Supported

Table 5- Model fit results

Variable	Coefficient of determination (R^2)	Redundancy index (Q^2)	Communality index	Goodness of fit (GOF)
Government Policies and Regulations	–	–	0.711	0.558
Acceptance of Smart Agriculture Technologies	–	–	0.685	
Workforce Force Consequences	0.456	0.253	0.590	
Economic Consequences	0.382	0.198	0.615	
Environmental Consequences	0.610	0.343	0.625	

According to Table 5, the «coefficient of determination» index is used to connect the measurement model and the structural model in structural equation modeling. This criterion indicates the effect that an exogenous variable has on an endogenous variable. The values 0.19, 0.33, and 0.67 are defined as the thresholds for weak, moderate, and strong levels of the coefficient of determination, respectively. Additionally, the redundancy index determines the predictive power of the model. For the strength of the model's predictive power regarding endogenous constructs, the values 0.02, 0.15, and 0.35 can be considered as thresholds for weak, moderate, and strong predictive power, respectively

(Deljo *et al.*, 2021). Therefore, Table 5 shows favorable results for these criteria. To evaluate the quality of measurement models in the PLS method, an index called the "communality index" can be used. This criterion indicates how much of the variability of the indicators (questions) is explained by their related construct. Positive values of this index represent an appropriate and acceptable quality of the measurement model (Deljo *et al.*, 2021). Therefore, Table 5 presents the output of this criterion from the Smart-PLS software, indicating the appropriate quality of the measurement model. It is worth noting that, in this study, the Goodness of Fit (GOF) index was used to assess the overall model fit. Three values, namely 0.01, 0.25, and 0.36, are introduced as weak, moderate, and strong levels for the GOF index, respectively. The higher the value of this index, the better the overall fit of the model can be considered. Therefore, Table 5 shows the values of this index, and the result indicates the high strength of the model with a value of 0.558.

Discussion and Analysis

The results of the examination of the first research hypothesis showed that the adoption of smart farming technologies has a positive and significant effect on workforce-related outcomes. Regarding the confirmation of the aforementioned hypothesis, it can be stated that the adoption of smart farming technologies is an important driver of workforce-related outcomes; in other words, the adoption of smart farming technologies can facilitate agricultural activities such as farmers' stress, workload, and working hours, thereby improving farmers' well-being. This finding is consistent with the results of studies by, among others, Yamoah & Kaba, 2024; Nanseki, 2022; Mamilianti, 2020. On the other hand, based on the test of the second research hypothesis, it was determined that there is a positive relationship between the adoption of smart farming technologies and economic outcomes. In fact, the adoption of smart farming technologies directly affects economic outcomes. Accordingly, the adoption of smart farming technologies provides multiple economic benefits for both farmers and the national economy (GDP). The use of smart farming technologies increases productivity, income, and product quality. In other words, these technologies make agricultural activities more efficient and effective, allowing producers (farmers) to increase productivity and produce more high-quality products using fewer resources. This finding is consistent with the results of studies such as Kasimati *et al*., 2024; Yamoah & Kaba, 2024; Nanseki & Chomei, 2023; Pal *et al.*, 2022. It is worth mentioning that the confirmation of the third research hypothesis indicates that the positive effect of adopting smart farming technologies extends to environmental outcomes. Accordingly, smart farming technologies can help farmers produce crops more efficiently while protecting the environment and natural resources. Reducing the use of fertilizers, pesticides, irrigation water, and greenhouse gas emissions are attributed to the environmental outcomes of adopting smart farming technologies. Therefore, by using these technologies, natural resources such as water, soil, and energy can be used optimally, enabling farmers to operate in an environmentally sustainable manner. This finding is consistent with the results of studies such as Yamoah & Kaba, 2024; Kasimati *et al*., 2024. Furthermore, the data analysis and interpretation regarding the confirmation of hypotheses four, five, and six of the study highlight the moderating role of government policies and regulations in the relationship between the adoption of smart farming technologies and workforce, economic, and environmental outcomes. Government support plays a crucial role in facilitating the adoption of smart farming technologies. Government support, which includes providing subsidies for inputs such as the procurement of smart farming technologies, offering comprehensive information and appropriate training programs for farmers, as well as imposing low taxes on imported smart farming technologies, can create favorable conditions for the adoption of these technologies and, consequently, their various outcomes. These results are consistent with the findings of studies such as Islam *et al*., 2024; Jaroenwanit *et al*., 2023; Azam & Shaheen, 2018; Aryal *et al*., 2018; Amondo & Simtowe, 2018.

Conclusion

The aim of the present study was to examine the outcomes of adopting smart farming technologies, considering the moderating role of government policies and regulations, among managers, specialists, and experts in the agricultural sector of Tehran and Alborz provinces, Iran. The results of the data analysis showed that the first hypothesis of the study, which stated that the adoption of smart farming technologies has a positive and significant effect on workforce -related outcomes, was supported. Similarly, the first hypothesis has also been confirmed in studies such as Yamoah & Kaba, 2024; Nanseki, 2022; Mamilianti, 2020. The results of the data analysis showed that the second and third hypotheses of the study, which respectively stated that the adoption of smart farming technologies has a positive and significant effect on economic and environmental outcomes, were supported. The second hypothesis has also been confirmed in studies such as Kasimati *et al*., 2024; Yamoah & Kaba, 2024; Nanseki & Chomei, 2023; Pal *et al*., 2022, while the third hypothesis has been supported in studies by Yamoah & Kaba, 2024; Kasimati *et al*., 2024. Furthermore, the fourth, fifth, and sixth hypotheses of the study, which indicate the moderating role of government policies and regulations in the relationship between the adoption of smart farming technologies and workforce, economic, and environmental outcomes, were confirmed. The results of these three hypotheses have also been supported in previous studies such as Islam *et al*., 2024; Jaroenwanit *et al*., 2023; Azam & Shaheen, 2018; Aryal *et al*., 2018; Amondo & Simtowe, 2018.

Managers, specialists, and experts in the agricultural sector play a major role in this field. As climate change occurs—meaning that everything is changing—the production system must adapt accordingly. Therefore, in line with the confirmed positive effects of adopting smart farming technologies on workforce, economic, and environmental outcomes, it is recommended that managers, specialists, and experts in the agricultural sector establish research centers for artificial intelligence and big data and engage in useful activities related to smart farming technologies. In fact, they should facilitate the dissemination of knowledge or new knowledge within the country. They should also develop new models and patterns to ensure that enough food can be supplied for the country in the coming years. They should collect accurate and reliable data by utilizing artificial intelligence technologies in order to develop new models. They should also properly analyze the past so that they can shape the future. It is also recommended to participate in national artificial intelligence events related to the agricultural sector. Therefore, if these actions are implemented, the workforce, economic, and environmental benefits of smart farming technologies can be realized. On the other hand, regarding the confirmation of the moderating role of government policies and regulations in the relationship between the adoption of smart farming technologies and workforce, economic, and environmental outcomes, it is recommended that policymakers provide incentives such as subsidies to facilitate access like smart farming technologies and thereby enhance their affordability. Moreover, by implementing training programs, comprehensive information regarding the use of smart farming technologies should be provided to farmers along with certification; this means that accessible information channels—such as agricultural extension services, workshops, seminars, and online resources—help enhance farmers' understanding of the potential benefits and performance of smart farming technologies.

One of the fundamental limitations of the present study is that the conditions for the use and adoption of smart farming technologies are not the same or similar across all provinces. Therefore, caution should be exercised when generalizing the study's results to other provinces. On the other hand, managers, specialists, and experts in the agricultural sector had sufficient knowledge about the concepts of technology adoption, artificial intelligence, and smart farming; however, due to the novelty of smart farming technologies, they were not sufficiently familiar with the specific concept of smart farming technology adoption. In addition to the limitation, the existing literature on the moderating role of government policies and regulations in the relationship between the adoption of smart farming technologies and workforce, economic, and environmental outcomes was scarce and limited. It should be noted that the researchers' access to domestic studies was very limited, given the new and emerging nature of smart farming technology adoption in the theoretical literature. Finally, the use of a questionnaire for data collection is considered another limitation of the present study, as not all respondents had the same understanding of the questionnaire items, and the researchers had no control over the level of accuracy and motivation of the respondents when answering the questions.

Considering the aforementioned limitations, it is suggested that future researchers examine the research model in companies operating in Iran, such as knowledge-based companies in the field of smart agriculture. Furthermore, a comparative approach could be used to compare the results of different studies, and ultimately to present the resulting managerial and operational recommendations. Additionally, future researchers are advised to thoroughly test and examine the current research model using qualitative methods, such as the grounded theory approach, in active provinces within the agricultural sector.

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مقاله پژوهشی
جلد ۴۰، شماره ۲، تابستان ۱۴۰۵، ص. ۱۵۰-۱۲۹

مطالعۀ پیامدهای پذیرش فناوری‌های کشاورزی هوشمند با نقش تعدیلگر سیاست‌ها و مقررات دولتی

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تاریخ دریافت: ۱۴۰۴/۰۴/۲۶
تاریخ پذیرش: ۱۴۰۵/۰۱/۳۰

چکیده

بخش کشاورزی یکی از حوزه‌هایی است که فناوری‌های کشاورزی هوشمند در آن کاربرد زیادی دارند. فناوری‌های کشاورزی هوشمند پتانسیل تجزیه وتحلیل داده‌های کشاورزی را در مقیاسی ارائه می‌دهند که قبلاً امکان‌پذیر نبود. پذیرش فناوری‌های کشاورزی هوشمند پتانسیل بهبود بهره‌وری و سودآوری در کشاورزی را دارد و در عین حال پایداری را نیز بهبود می‌بخشد. دستیابی به این پتانسیل نه تنها به پیشرفت تکنولوژی نیاز دارد، بلکه نیازمند درک دقیق پیامدهایی است که پذیرش فناوری‌های کشاورزی هوشمند بر آنها تأثیر می‌گذارد. با توجه به توضیحات مذکور، پراکندگی پژوهش‌های قبلی و نبود نگاه جامع، هدف پژوهش حاضر، مطالعۀ پیامدهای پذیرش فناوری‌های کشاورزی هوشمند با نقش تعدیلگر سیاست‌ها و مقررات دولتی است. جامعۀ آماری پژوهش شامل مدیران، کارشناسان و خبرگان حوزۀ کشاورزی هوشمند در استان تهران و البرز است. یکی از روش‌های تعیین حداقل حجم نمونه، روش نسبت تعداد اعضای نمونه به تعداد سؤالات مدل پژوهش یا نظریۀ N:q است که حداقل نسبت پیشنهادی توسط جکسون است. بر همین اساس با توجه به تعداد گویه‌های پرسش‌نامه (۲۷ سؤال)، حجم نمونه ۲۷۰ نفر برآورد شد. ابزار گردآوری داده‌ها پرسش‌نامه است. روایی پرسشنامه به‌صورت تشخیصی، هم‌گرا و واگرا و پایایی پرسشنامه نیز با ضریب آلفای کرونباخ و پایایی ترکیبی بررسی شد. آزمون مدل پژوهش براساس روش حداقل مربعات جزئی و به کمک نرم‌افزار Smart - PLS 3 انجام شد. نتایج تجزیه‌وتحلیل داده‌ها نشان داد که پذیرش فناوری‌های کشاورزی هوشمند بر پیامدهای نیروی کار، اقتصادی و زیست‌محیطی تأیر مثبت و معنادار دارد. علاوه بر این، سیاست‌ها و مقررات دولتی در ارتباط بین پذیرش فناوری‌های کشاورزی هوشمند و پیامدهای نیروی کار، اقتصادی و زیست‌محیطی نقش تعدیلگر مثبت دارد.

واژه‌های کلیدی: پذیرش فناوری، پیامدهای اقتصادی، پیامدهای زیست‌محیطی، پیامدهای نیروی کار، کشاورزی هوشمند

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https://doi.org/10.22067/jead.2026.94497.1364

Journal of Agricultural Economics & Development

Homepage: https://jead.um.ac.ir

Research Article
Vol. 40, No. 2, Summer 2026, p. 151-172

Decision-Making in the Water-Energy-Food-Environment Nexus: Pathways to Sustainable Agricultural Development

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Received: 21 September 2025 Revised: 28 November 2025 Accepted: 27 December 2025 Available Online: 27 December 2025	**How to cite this article:** Fakhroldin, R.A., Mirzaei, A., Taki, M., & Azarm, H. (2026). Decision-making in the water-energy-food-environment nexus: Pathways to sustainable agricultural development. *Journal of Agricultural Economics & Development, 40*(2), 151-172. https://doi.org/10.22067/jead.2025.95571.1378

Abstract

We have strived to present a fresh definition of the water-energy-food-environment-decision makers (WEFED) nexus through the creation of a comprehensive and interconnected system. In this study, we considered criteria for consumption, mass productivity, and economic productivity related to irrigation water, renewable and non-renewable energy, as well as the criteria of fertilizer and pesticide use, CO_2 emissions, and wetland conservation to elucidate the water-energy-food-environment (WEFE) nexus. We then assessed the impact of decision-makers' perspectives on the nexus criteria under seven different management scenarios: water consumption management (WCM), energy consumption management (ECM), water economic management (WEM), energy economic management (EEM), environmental management (ENM), management with equal weight given to criteria (WEFE), and management with weight based on the opinions of decision makers in the study area (WEFED), employing TOPSIS method. To explicitly integrate decision-makers' perspectives into this system (the WEFED approach), the weights assigned to each sustainability criterion in one scenario were determined directly based on a survey of local decision-makers using the Fuzzy Analytical Hierarchical Process (FAHP) method. The study findings revealed that in the WCM, ECM, and ENM scenarios, barley cultivation held the highest priority, yet despite improvements in environmental parameters, a decrease in water and energy economic productivity was observed compared to the current pattern. Conversely, in the WEM and EEM scenarios, tomato cultivation took precedence, and despite the deterioration of environmental conditions, enhanced mass and economic water and energy productivity were demonstrated compared to the current pattern. The discrepancy in results among the various sustainable scenario patterns underscored the substantial impact of decision-makers' perspectives on sustainable agricultural management. Finally, it was determined that the WEFE scenario returned the greatest number of improvements (11 out of 13 criteria) in sustainable management criteria compared to the current pattern. Therefore, the findings revealed that a holistic, equally-weighted nexus approach (WEFE), while increasing water consumption, delivers the most balanced sustainability outcomes, though its implementation must be coupled with robust water governance.

Keywords: CO_2 emission, Sustainability perspectives, Water and energy economic management, Wetland conservation

https://doi.org/10.22067/jead.2025.95571.1378

Introduction

Achieving sustainable development goals (SDGs) is possible through sustainable food production and the efficient use of water and energy resources within food systems (UN, 2023; Mirzaei *et al*., 2024a). The agricultural sector, as the primary provider of food security, heavily relies on water and energy resources, with limited substitutability with other inputs in this sector (Sadeghi *et al*., 2020; Zuo *et al*., 2021; Radmehr *et al*., 2021). The expansion of agricultural production has exacerbated the strain on water resources, energy, the environment, and natural ecosystems like wetlands (Pastor *et al*., 2019; Abdelkader & Elshorbagy, 2021; Mirzaei & Zibaie, 2021; Mirzaei *et al*., 2022). In Iran, as a developing country, the agricultural sector contributes to approximately 10% of the GDP, over 20% of non-oil exports, and employs around 20% of the workforce (Farajian *et al*., 2018; Karamian *et al*., 2023).

Access to clean water and water management are at risk due to increasing climate-related disasters and the fact that several regions are facing severe water scarcity (UN, 2023). The agricultural sector is the dominant consumer of water in Iran. While many studies estimate its share of total water withdrawals in normal years to be between 80% and 90% (Keshavarz *et al*., 2021; Zad-Parsa *et al*., 2024), some research reports a higher figure of approximately 92% (Mohammad Jani & Yazdanian, 2014; Mirzaei *et al*., 2024b). It is important to note that this share can be significantly lower during drought periods. Despite this variability, Iran's agricultural water consumption remains substantially higher than regional and global averages- around 84% for the Middle East and 69% for the rest of the world (Mohammad Jani & Yazdanian, 2014; Mirzaei *et al*., 2024b). Research conducted by the International Water Management Institute predicts that many regions worldwide will face freshwater scarcity issues by 2025. Iran is among the countries grappling with a severe water crisis, which has been intensified by increasing demand, declining water quality, low prices, and inadequate water resource management (Madani *et al*., 2016; Saray & Haghighi, 2023). Moreover, over the past 23 years, Iran has experienced rising temperatures, reduced rainfall, and subsequent depletion of water resources, exacerbating the water crisis (National Climate Change Office, 2010).

The industrialization of agriculture and the excessive use of fertilizers, pesticides, and other high-energy inputs, such as fossil fuels, electricity, and machinery, have resulted in a growing consumption of non-renewable energy and the release of greenhouse gases (Li *et al*., 2016; Masaeli *et al*., 2023). In 2019, fossil fuels were identified by the International Energy Agency (IEA) as the primary source of energy worldwide, contributing to over 81% of global energy production (IEA, 2021). Developing countries are experiencing a 9.6% annual growth rate in renewable energy installation; however, despite substantial needs, international financial flows for clean energy continue to decline (UN, 2023). This heavy reliance on fossil fuels as a non-renewable energy source for Iran's energy supply will further worsen the energy crisis (Zolghadr-Asli *et al*., 2023). Additionally, in the agricultural sector alone, Iran consumes over 36 million kilowatt-hours of electricity, accounting for more than 15% of the country's total electricity consumption (Mirzaei *et al*., 2024b). Consequently, transitioning from fossil fuel-based energy systems to renewable sources and moving towards green growth are imperative to meet the objectives of the energy-food nexus (Mahdavian *et al*., 2022).

The review of literature highlights that previous studies have often taken a simplistic and sometimes incomplete approach when considering the interconnectedness of water, energy, and food resources (Martinez-Hernandez *et al*., 2017; Jalilov *et al*., 2018; Zhou *et al*., 2019). For instance, in the energy sector, there has been a predominant focus on hydropower generation, neglecting other forms of energy (Zhou *et al*., 2019). The examination of energy consumption types, including fossil fuel-based sources like coal, crude oil, natural gas, and renewable energies, has been insufficiently addressed within the context of the Water-Energy-Food (WEF) nexus in previous studies (Wu *et al.*, 2021). Furthermore, some studies have primarily concentrated on the water component, aiming to maximize gross margin and optimize water allocation in agricultural patterns (Garg & Dadhich, 2014; Zhang & Guo, 2016). Nevertheless, researchers now argue that all sustainability criteria pertaining to water, energy, and food resources should be quantified within the framework of the WEF nexus (Karamian *et al.*, 2021; Radmehr *et al.*, 2021).

The WEF nexus aims to achieve sustainable utilization of water, energy, and food resources while enhancing their security through integrated management and consideration of stakeholders' goals and interests in various sectors (Leck *et al.*, 2015; Salam *et al.*, 2017; Taguta *et al.*, 2022). The conceptualization of the WEF nexus has shown significant variation in previous studies, depending on the industry being investigated and the objectives and methods employed (FAO, 2014; Nahidul Karim & Daher, 2021). Within the agricultural sector, the WEF nexus concept has been applied in various studies (El-Gafy, 2017; Li *et al.*, 2019; Sadeghi *et al.*, 2020; Jagadeesh & Sampath, 2022). Furthermore, studies related to the WEF nexus approach commonly utilize multi-objective optimization methods (Jalilov *et al.*, 2016; Stamou & Rutschmann, 2018; Zhang *et al.*, 2018; Si *et al.*, 2019; Hu *et al.*, 2019; Sun *et al.*, 2020; Ji *et al.*, 2020; Yu *et al.*, 2020).

In recent times, there has been a disregard for the environment and natural ecosystems within the WEF framework, resulting in insufficient attention being given to this crucial aspect. However, it is imperative to recognize the significance of environmental goals in order to effectively implement the WEF concept and measure sustainability in the agricultural sector (Mirzaei *et al.*, 2022; Saray *et al.*, 2022). Disturbing statistics and information reveal the improper use of fertilizers and chemical pesticides, leading to their accumulation in agricultural products and positioning Iran at the 123rd rank out of 180 countries worldwide (Iran Food and Drug Administration, 2016). Furthermore, Iran's greenhouse gas emissions present an unfavorable situation, with a mere 0.52% contribution to the world's gross domestic product and an annual production of 1.65% of global greenhouse gas emissions, placing the country tenth on a global scale (World Resources Institute, 2015). Another critical aspect of environmental conservation involves the protection and restoration of wetlands. The condition of wetlands in Iran highlights a severe crisis characterized by their drying and the subsequent environmental ramifications resulting from conflicting water usage between the agricultural sector and wetlands (Mirzaei & Zibaie, 2021). Consequently, the lack of attention towards environmental issues poses numerous challenges to successfully implementing the WEF concept and maintaining the credibility of its outcomes. However, a review of the existing literature indicates limited research efforts addressing the weaknesses in the connection between WEF and environmental concerns. For example, Mirzaei *et al.* (2022) attempted to mitigate these weaknesses by incorporating the objective of minimizing the use of fertilizers and chemical pesticides alongside the WEF goals. Similarly, Saray *et al.* (2022) and Masaeli *et al.* (2023) have focused on reducing CO_2 emissions in the agricultural production process while aligning with the objectives of the WEF. Mirzaei *et al.* (2024b) added CO_2 emissions and water salinity as environmental criteria to the water-energy-food nexus and determined the relationships between these criteria and other components of the nexus.

Literature paid little attention to the divergent perspectives of regional decision-makers when it comes to implementing the WEF nexus, the complex quantification of nexus within mathematical programming models, and the inflexibility of these models in measuring qualitative criteria (Mirzaei *et al.*, 2023). In contrast, the use of multi-criteria decision-making methods, as opposed to multi-objective mathematical programming methods, allows for the easy formulation of complex issues and diverse objectives, while considering the opinions and perspectives of various experts and decision-makers, ultimately deriving appropriate solutions (Nehamo *et al*., 2020; Mirzaei *et al*., 2023). The use of multi-criteria decision-making methods such as TOPSIS addresses the critical gap in managing qualitative environmental criteria within the WEF nexus framework, fundamentally distinguishing it from the multi-objective optimization models prevalent in prior works (e.g., Radmehr *et al*., 2021). While optimization models excel at finding solutions based on quantitative constraints and objective functions, they often struggle to formally incorporate qualitative judgments and stakeholder preferences. In contrast, the TOPSIS method is uniquely suited for this task, as it enables the direct integration of both quantitative data and qualitative expert assessments into a unified analytical framework.

In general, in this study, we aim to utilize multi-criteria decision-making methods and consider the perspectives of various experts, as well as incorporate quantitative and qualitative environmental criteria, to determine sustainable resource allocation patterns for the WEF nexus. Thus far, no comprehensive research has been conducted that simultaneously takes into account all decision-makers' perspectives and all objectives of the WEF nexus index in conjunction with environmental goals, such as reducing non-renewable energy consumption, minimizing chemical pollution, decreasing CO_2 emissions, and protecting wetlands. Therefore, the conceptual framework of this study can be considered as a novel approach in the sustainable resource management of the agricultural sector. Consequently, the primary novelty of this work lies not merely in combining elements, but in creating a transparent, flexible, and stakeholder-informed decision-support tool that is specifically designed to elucidate and navigate the complex trade-offs between economic productivity, resource efficiency, and environmental conservation in contested landscape. The results of this study can address the fundamental question of how important it is to consider different objectives and perspectives in elucidating sustainable patterns in the agricultural sector, and what pattern can provide the most desirable sustainable management.

Methodology

We employed a five-step approach, based on a thorough literature review, to establish sustainable patterns in the agricultural sector of the study area (Fig. 1). Initially, we identified and evaluated six criteria pertaining to the interconnections of the WEF nexus index in agriculture. These criteria encompassed irrigation water consumption, energy consumption, water mass productivity, energy mass productivity, water economic productivity, and energy economic productivity. This assessment was conducted through an extensive review of literature and data extraction from the study area (El-Gafy *et al*., 2017; Nhamo *et al*., 2020; Mirzaei *et al*., 2023). To conduct a more comprehensive analysis of the WEF nexus, we categorized the energy-related criteria into renewable and non-renewable energy. In the third step, we established the interconnections between environmental objectives and nexus elements using three criteria: wetland conservation (water-environmental linkages) (Mirzaei & Zibaei, 2021), reduction of chemical pollution (food-environmental linkages) (Mirzaei *et al*., 2022), and reduction of CO_2 emissions (energy-environmental linkages) (Saray *et al*., 2022; Saray & Haghighi, 2023). The fourth step entailed determining and calculating the weights of different criteria of WEFE nexus index, based on the insights of regional decision-makers. Finally, we computed the closed index (new index) using the TOPSIS method and extracted sustainable patterns, considering diverse expert perspectives.

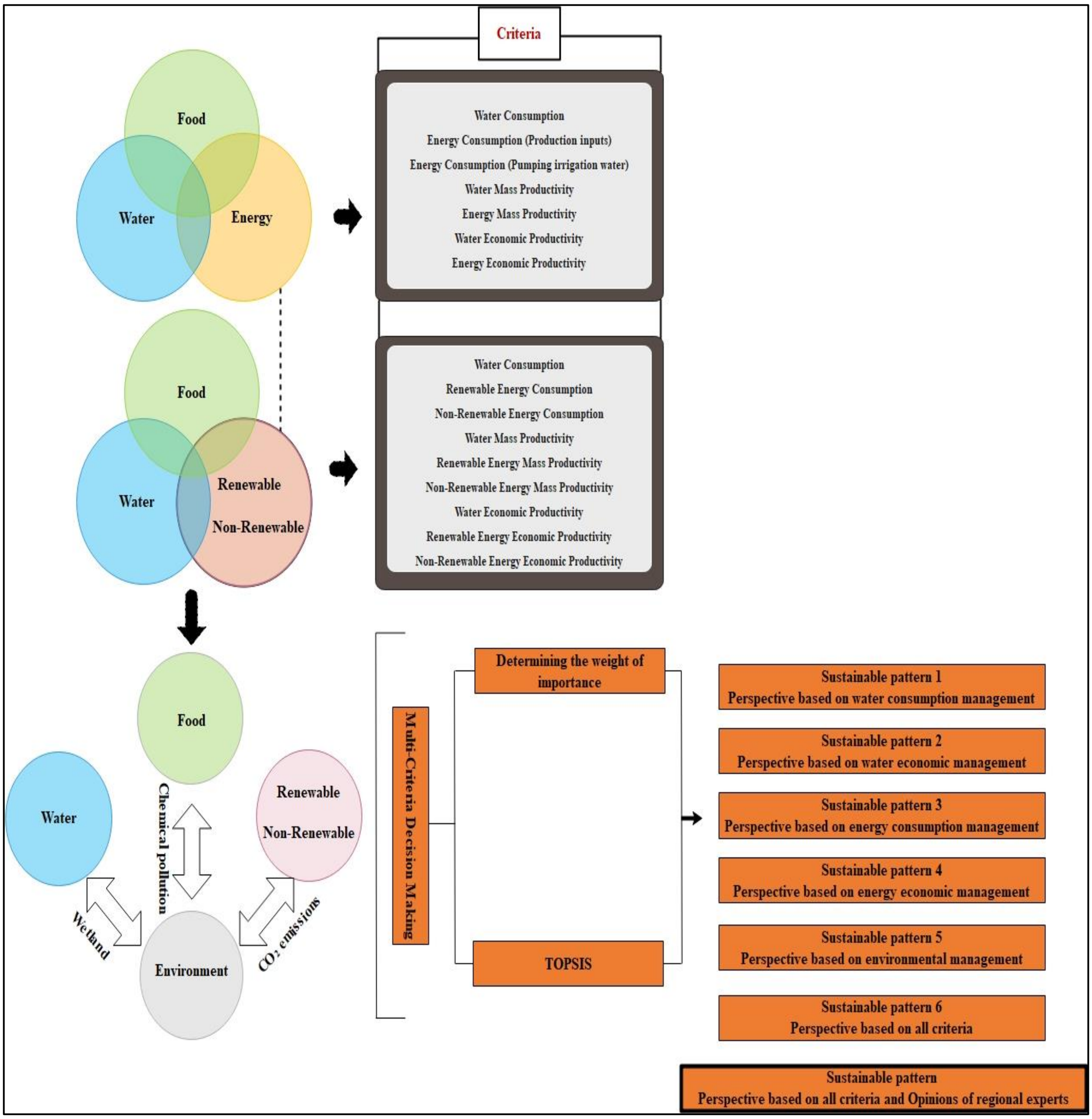

Figure 1- Proposed water-energy-food-environment-decision making nexus approach and assessment steps

Study Area

The study data was extracted from Shadegan Plain, located in Khuzestan Province, Iran (Fig. 2). Shadegan Plain is renowned as the largest plain in Khuzestan Province, spanning from 30° to 31° 33′ North, and 48° 17′ to 49° 49′ East. Wheat, barley, tomato, broad bean, and okra are among the main crops cultivated in this plain, with a significant portion of the land dedicated to wheat cultivation. Shadegan Wetland is situated in the southwest of Iran within this plain, approximately 60 kilometers south of Ahvaz, the capital of Khuzestan Province, and 5 kilometers south of Shadegan city.

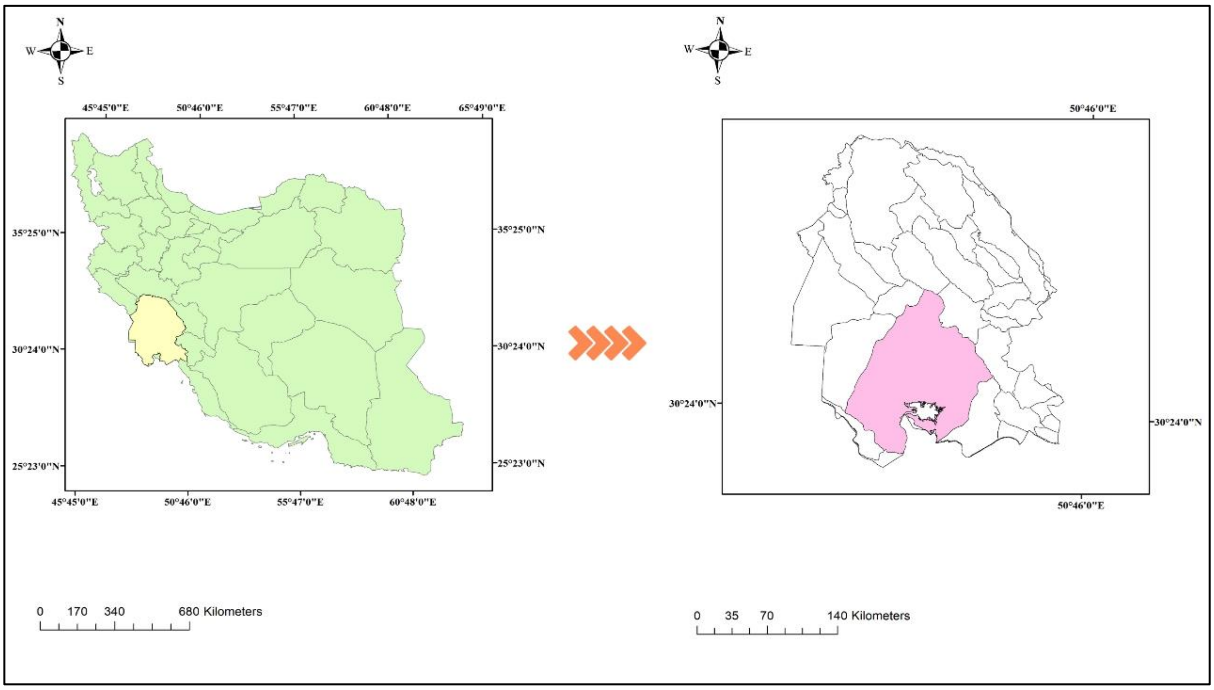

Figure 2- The geographical location of the studied area

Criteria of WEF Index

Water and food nexus indicators comprise irrigation water consumption, water mass productivity, and water economic productivity. A questionnaire was administered to the farmers, seeking details on the number of irrigation cycles, duration of each cycle, and the diameter or flow rate of the irrigation pipes. Utilizing their responses, the water consumption for each crop grown by the farmers was calculated. Consequently, the average water consumption per unit area (hectare) was determined for each crop in Shadegan Plain. The water mass productivity (WP) indicator, categorized by crop (C), was computed by dividing the crop yield (Y) per unit area (kilograms per hectare) by the water consumption of the crop (W) per unit area (cubic meters per hectare), based on equation (1) (El-Gafy, 2017):

$$WP_C = \frac{Y_C}{W_C} \quad (1)$$

To calculate the water economic productivity (WEP) indicator, it is necessary to compute the gross margin (GM) separately for each crop (C):

$$GM_C = (P_C.Y_C) - (\sum_{X=X1}^{Xn} P_X.X) \quad (2)$$

In equation (2), P_C and P_X represent the price per unit of the produced crop (dollars per kilogram) and the prices of input factors (*X=X1, X2, ..., Xn*) utilized in production. It is important to note that the prices of input factors vary depending on the type of input and may have different units. For instance, the price of seeds and fertilizers is measured in dollars per kilogram of input, while the price of machinery and labor is measured in dollars per hour of usage. Y and X indicate the yield of the crops per unit area (kilograms per hectare) and the consumption of different inputs per unit area, respectively. Therefore, the WEP is derived using equation (3). Equation (3) demonstrates that WEP (dollars per cubic meter) represents the ratio of the gross margin per unit area (dollars per hectare) to the water consumption per unit area (cubic meters per hectare).

$$WEP_C = \frac{GM_C}{W_C} \quad (3)$$

Energy-food nexus indicators encompass the utilization of renewable energy pertaining to labor, seeds, and animal manure, along with the utilization of non-renewable energy associated with chemical fertilizers, pesticides, fossil fuels, and machinery. Both the energy mass productivity of renewable and non-renewable energy sources, as well as the energy economic productivity, are taken into consideration. In order to compute the energy consumption in the production of diverse crops, the energy equivalent (ec) is considered for each unit of input consumption (Table 1). Subsequently, the renewable energy consumption (E1) and non-renewable energy consumption (E2) for the chosen sample farms per unit area (measured in MJ per hectare) are calculated by multiplying the coefficients in Table 1 with the quantities of input consumption (Kitani, 1999).

$$\mathrm{E1}_c = (\mathrm{labor}_c.\mathrm{ec}_{\mathrm{labor}}) + (seed_c.\mathrm{ec}_{\mathrm{seed}}) + (manure_c.\mathrm{ec}_{\mathrm{manure}}) \quad (4)$$

$$\mathrm{E2}_c = (\mathrm{fertilizer}_c.\mathrm{ec}_{\mathrm{fertilizer}}) + (pesticide_c.\mathrm{ec}_{\mathrm{pesticide}}) + (fuel_c.\mathrm{ec}_{\mathrm{fuel}}) + (machinary_c.ec_{machinary}) \quad (5)$$

Table 1- Energy equivalent (ec) to the inputs used in the production of crops

Inputs	Unit	Energy equivalent (MJ)	References
Labor	h	1.96	Khanali *et al.*, 2021; Sarbijan *et al.*, 2025
Nitrogen fertilizer	kg	78.1	Khoshnevisan *et al.*, 2013
Phosphate fertilizer	kg	17.4	Khoshnevisan *et al.*, 2013
Potassium fertilizer	kg	13.7	Khoshnevisan *et al.*, 2013
Micronutrient fertilizer	kg	120	Khoshnevisan *et al.*, 2013
Livestock manure	kg	0.3	Tabatabaei *et al.*, 2013
Insecticides	l	115	Khoshnevisan *et al.*, 2014
Herbicides	l	85	Khoshnevisan *et al.*, 2014
Fungicides	l	295	Khoshnevisan *et al.*, 2014
Disel fuel	l	47.8	Rajaiefar *et al.*, 2014
Electricity	kwh	11.93	Kaab *et al.*, 2019
Machinery	h	62.7	Sadeghi *et al.*, 2020; Sarbijan *et al.*, 2025
Wheat seed	kg	15.7	Soltani *et al.*, 2013
Barley seed	kg	14.7	Ozkan *et al.*, 2004
Broad bean seed	kg	14.7	Ozkan *et al.*, 2004
Okra seed	kg	0.8	Tuti *et al.*, 2012
Tomato seed	kg	1	Esengun *et al.*, 2007

The energy mass productivity indicators for renewable energy (E1P) and non-renewable energy (E2P), categorized by crops (C), express the relationship between crop yield (Y) per unit area (kilograms per hectare) and the consumption of renewable energy (E1) and non-renewable energy (E2) per unit area of the crop (MJ per hectare). These indicators can be computed using equations (6) and (7) (El-Gafy, 2017):

$$E1P_C = \frac{Y_C}{E1_C} \quad (6)$$

$$E2P_c = \frac{Y_C}{E2_C} \quad (7)$$

Moreover, the energy economic productivity indicators for renewable energy (E1EP) and non-renewable energy (E2EP) are calculated by dividing the GM per unit area (dollars per hectare) by the consumption of renewable energy (E1) and non-renewable energy (E2) per unit area of the crop (MJ per hectare). These indicators can be computed using equations (8) and (9).

$$E1EP_C = \frac{GM_C}{E1_C} \quad (8)$$

$$E2EP_C = \frac{GM_C}{E2_C} \quad (9)$$

Environmental criteria and WEF index

Four environmental indicators, including the fertilizers consumption, pesticides consumption, CO_2 emissions, and wetland conservation, have been identified to reflect the interconnectedness between the environment and food, energy, and water. Data on fertilizer and pesticide consumption, categorized by specific crops, were extracted from questionnaires completed by sampled farmers. The measurement of CO_2 emissions, also categorized by crops, was obtained by multiplying the input consumption by the corresponding CO_2 emission coefficient per unit of input (Table 2).

Table 2- CO_2 equivalent to the inputs used in the production of crops

Inputs	Unit	CO_2 equivalent (kg CO_2 eq)	References
Machinery	h	0.071	Dyer & Desjardins, 2007
Disel fuel	l	2.76	Dyer & Desjardins, 2007
Nitrogen fertilizer	kg	1.3	Lal, 2004
Phosphate fertilizer	kg	0.2	Lal, 2004
Pesticides	l	3.9	Lal, 2004
Electricity	kwh	0.608	Dyer & Desjardins, 2007

In order to evaluate the wetland conservation indicator, we employed expert-assessed data that was categorized according to specific crops. Experts assigned scores ranging from 1 to 9, based on the water consumption associated with each crop and the allocated water reserve for meeting the wetland's water rights. One crucial aspect to take into account is the intersection of two criteria irrigation water consumption and wetland conservation through water supply. It is evident that higher irrigation water consumption for a crop leads to a lower score for wetland conservation. This raises a potential concern regarding duplicated and redundant criteria in the calculations. However, if only irrigation water consumption is considered as a criterion, and the experts' perspective solely determines the weight of its importance, some respondents may solely focus on the concept of water consumption, time efficiency, and cost reduction, disregarding the impact of reducing water consumption on reserving more water to meet the wetland's water rights. Hence, to attain reliable results and minimize errors in the derived patterns, this criterion has also been incorporated in the analysis.

Table 3- Definition of scenarios

Scenarios	Perspectives	Allocated weights (definition of scenarios)
WCM	Water consumption management	The criterion of irrigation water consumption received the highest weight of importance (60%). The remaining weight (40%) was evenly distributed among the other 12 criteria (each criterion approximately 3.33%).
WEM	Water economic management	The criteria of water economic productivity, water mass productivity, and irrigation water consumption were given the highest weights of importance, in that order (30%, 20%, and 10% respectively). The remaining weight (40%) was evenly distributed among the other 10 criteria (each criterion accounting for 4%).
ECM	Energy consumption management	The criteria of renewable energy consumption (40%) and non-renewable energy consumption (20%) were given the highest weights of importance, in that order. The remaining weight (40%) was evenly distributed among the other 11 criteria (each criterion approximately 3.64%).
EEM	Energy economic management	The criteria of economic productivity of renewable energy (20%), economic productivity of non-renewable energy (20%), mass productivity of renewable energy (10%), and mass productivity of non-renewable energy (10%) were given the highest weights of importance, in that order. The remaining weight (40%) was evenly distributed among the other 9 criteria (each criterion approximately 4.44%).
ENM	Environmental management	The criteria of fertilizer consumption (15%), pesticide consumption (15%), CO_2 emissions (15%), and wetland conservation (15%) were given the highest weights of importance, in that order. The remaining weight (40%) was evenly distributed among the other 9 criteria (each criterion approximately 4.44%).
WEFE	Combination of perspectives with equal weights	All criteria are assigned equal weights (approximately 7.69% for each criterion).
WEFED	Decision-makers of the study area	The weights of all criteria be determined based on the opinions of regional decision-makers using the FAHP[1] method.

1- Fuzzy Analytical Hierarchical Process

TOPSIS Method and Extraction of Sustainable Patterns

In this study, we utilized the proposed WEFE (Water-Energy-Food-Environment) nexus criteria along with the TOPSIS method to extract sustainable patterns. The criteria encompassed 13 indicators, namely: irrigation water consumption, water mass productivity, water economic productivity, renewable energy consumption, non-renewable energy consumption, renewable energy mass productivity, non-renewable energy mass productivity, renewable energy economic productivity, non-renewable energy economic productivity, fertilizer consumption, pesticide consumption, CO_2 emissions, and wetland conservation. In the TOPSIS method, the initial step involved constructing a performance matrix and determining the weight assigned to each criterion. To establish these weights, we considered seven different scenarios (Table 3). Subsequently, we conducted a comparative analysis of the sustainable patterns obtained for different scenarios, thereby assessing the validity of the proposed approach.

In the TOPSIS method, we begin by normalizing the performance matrix without considering the units. Next, the normalized values of the performance matrix are multiplied by the weights assigned to each criterion, resulting in a weighted normalized performance matrix. Moving forward, the TOPSIS method, categorized as a compromise or consensus-based approach, chooses the option with the shortest distance from the ideal alternative as the best choice. The method follows these steps:

1) In the case of criteria aiming for maximum, the highest values are deemed the most favorable points for identification and ideal alternatives. Conversely, for criteria aiming for minimum, the lowest values are considered the best points for identification and ideal alternatives (A^+). This study considers water mass productivity, renewable and non-renewable energy mass productivity, water economic productivity, renewable and non-renewable energy economic productivity, and wetland conservation as positive performance criteria, where higher values are preferred. On the other hand, irrigation water consumption, renewable and non-renewable energy consumption, fertilizer and pesticide consumption, and CO_2 emissions are considered negative performance criteria, where lower values are preferred.

$$A^+ = \{A_1^+, A_2^+, \dots, A_j^+\} \tag{10}$$

2) For criteria that aim for maximum, the lowest value is considered the anti-ideal alternative (A^-). Conversely, for criteria that aim for minimum, the highest value is considered the anti-ideal alternative (A^-).

$$A^- = \{A_1^-, A_2^-, \dots, A_j^-\} \tag{11}$$

The closed index (CI) for each crop was calculated using equation (12).

$$CI = \frac{(R)^-}{(R)^+ + (R)^-} \tag{12}$$

Where R^- represents the distance of each alternative from the anti-ideal alternative, and R^+ represents the distance of each alternative from the ideal alternative. Subsequently, in order to assess the contribution of each crop to the sustainable cropping pattern, the standard CI will be employed. This involves dividing the CI of each crop by the sum of the CI_s of all pattern crops, and thereby calculating the proportionate share of each crop within the cropping pattern. It should be noted that the calculations for the TOPSIS method were performed using Microsoft Excel software.

Sampling

Using the Cochran formula, the sample size was estimated to be 68 farmers. These farmers were selected through a simple random sampling method, and the data were collected by completing face-to-face questionnaires with these farmers. To acquire the necessary data, 68 farmers from Shadegan Plain (selected randomly using the Cochran formula) were surveyed through questionnaires during the 2021-2022 cropping season. The collected data encompassed various aspects such as employed labor, machinery fuel, electricity, water pumping fuel, machinery, fertilizers, pesticides, water consumption, seeds, cost information of inputs, and product details (including crop yield, cultivated area, and price). To implement the FAHP and TOPSIS methods, a sample of 10 experts was also selected. The experts were selected using a purposive sampling method based on two main criteria: (1) their organizational affiliation and direct involvement in the management of water, agricultural, or environmental resources in the Shadegan Plain, and (2) a minimum of 10 years of relevant work experience in the region to ensure informed and reliable judgments.

Result and Discussion

Analysis of Water Component Criteria

Water consumption, water mass productivity, and water economic productivity were individually calculated for the production of five main crops in the region, namely wheat, barley, broad bean, okra, and tomato, as presented in Table 4. The findings reveal that barley, with an approximate water consumption of 4871 (M^3 per hectare) and okra, with approximately 45357 (M^3 per hectare), stand as the least and most water-intensive crops in terms of water resources, respectively. Tomato production exhibits the highest level of water mass productivity, with one cubic meter of water resulting in the production of 2.165 kilograms of tomato. Conversely, okra demonstrates the lowest water mass productivity, yielding an average of around 0.214 kilograms of okra per cubic meter of water. The calculated water economic productivity points out that tomato generate the highest economic profit, amounting to $0.379 per cubic meter of water. Conversely, barley exhibits the lowest water economic productivity, with an economic return of $0.151 per cubic meter of water. Overall, it can be concluded that tomato possess a more favorable status compared to other crops in terms of water productivity and economic efficiency. The significant water mass productivity of tomato has also been supported by other studies (El-Gafy *et al*., 2017; Mirzaei *et al*., 2022). As for barley, despite its low water consumption, it falls short in terms of economic viability compared to other crops in the pattern, resulting in the lowest water economic productivity. This finding aligns with previous studies conducted on Iranian farms (Sadeghi *et al*., 2020; Saray *et al*., 2022; Masaeli *et al*., 2023).

Table 4- Values of water component criteria in the proposed WEFE nexus

Crops	Irrigation water consumption (M^3/he)	Water mass productivity (Kg/M^3)	Water economic productivity ($/$M^3$)
Wheat	7160.96	0.674	0.183
Barley	4871.34	0.821	0.151
Broad bean	7208	0.370	0.159
Okra	45356.57	0.214	0.203
Tomato	20418.63	2.165	0.379

Analysis of Energy Component Criteria

The energy consumption shares resulting from the use of various inputs for the production of the 5 main crops in the study area are presented in Fig. 3. The findings indicate that fertilizers and fuel for machinery have the highest energy consumption shares for wheat and barley, respectively. According to the obtained results, these two inputs account for over 65% of the total energy consumption. Specifically, the energy consumption share of fertilizers for wheat and barley production is approximately 36.60% and 34.51%, respectively, while the energy consumption share of fuel for machinery is approximately 31.28% and 29.90%, respectively. Moreover, the results reveal that fuel for water pumping and fertilizers have the highest energy consumption shares for the production of three crops: broad bean, okra, and tomato. The fuel share for water pumping accounts for roughly 51%, 51%, and 60% of the energy consumption in the production of broad bean, okra, and tomato, respectively. Similarly, the input share of fertilizers in energy consumption is approximately 26%, 25%, and 34% for the production of these crops, respectively. Previous studies have consistently demonstrated that fertilizers and diesel fuel are the primary contributors to energy consumption in agricultural production systems (Hülsbergen *et al*., 2001; Saray *et al*., 2022; Masaeli *et al*., 2023). Diesel fuel has particularly been identified as the most significant energy-consuming factor in crop production within the agricultural sector across various studies (Erdal *et al*., 2007; Pishgar-Komle *et al*., 2012; Zahedi *et al*., 2015; Saray & Haghighi, 2023).

The results demonstrate that the proportion of energy consumed from non-renewable sources for the production of all desired crops is significantly greater than the proportion derived from renewable energy (Fig. 4). For example, in the case of tomato and okra, renewable energy accounts for less than 2% of the total energy consumption, while non-renewable sources contribute to over 98% of the energy consumed. The barley exhibits the highest share of renewable energy consumption, making up approximately 12% of the total energy consumption. Consequently, it can be inferred that excessive reliance on non-renewable energy in the agricultural sector will exacerbate environmental challenges, a conclusion that aligns with findings from other studies (Asgharipour *et al*., 2016; Hua *et al*., 2016; Dimitrijević *et al*., 2020; Saray & Haghighi, 2023).

According to the results in Table 5, the highest amount of renewable energy has been consumed in the production of two crops, barley (approximately 3834 MJ per hectare) and wheat (approximately 3580 MJ per hectare). Meanwhile, the lowest amount of renewable energy has been consumed in the production of two crops, tomato and okra, which are approximately 834 and 1265 MJ per hectare, respectively. The highest amount of non-renewable energy consumption is related to the production of okra and tomato, with approximately 87454 MJ per hectare for okra and approximately 56920 MJ per hectare for tomato. The total amount of renewable and non-renewable energy consumption also shows that the production of barley and wheat requires less energy consumption, while the production of okra and tomato requires more energy consumption. The low energy consumption for the production of barley and wheat compared to other agricultural crops has been proven in several studies (Zahedi *et al*., 2015; Sadeghi *et al*., 2020; Mirzaei *et al*., 2022; Saray *et al*., 2022).

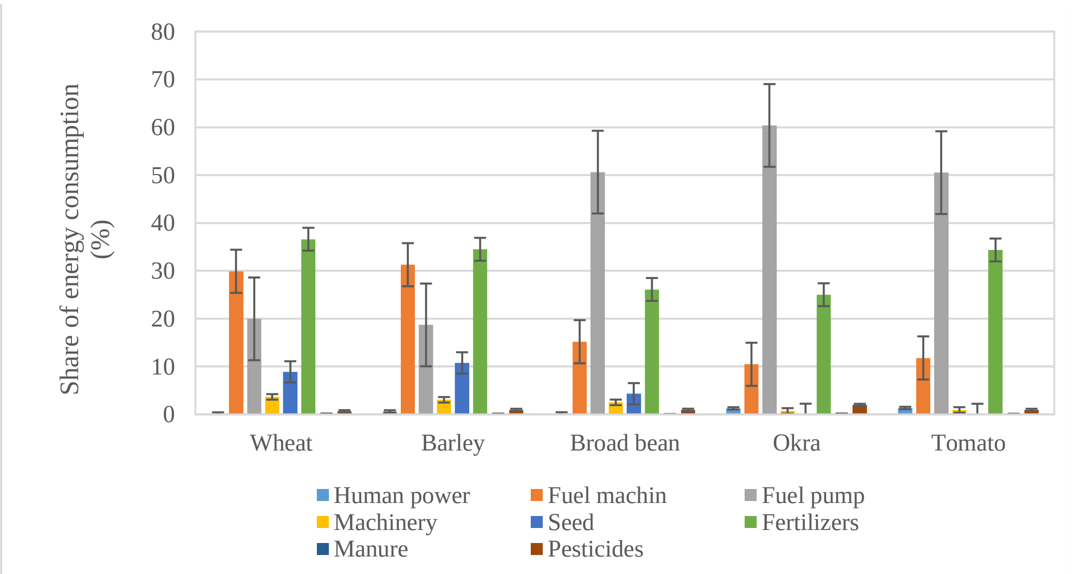

Figure 3- The distribution of energy consumption among different inputs

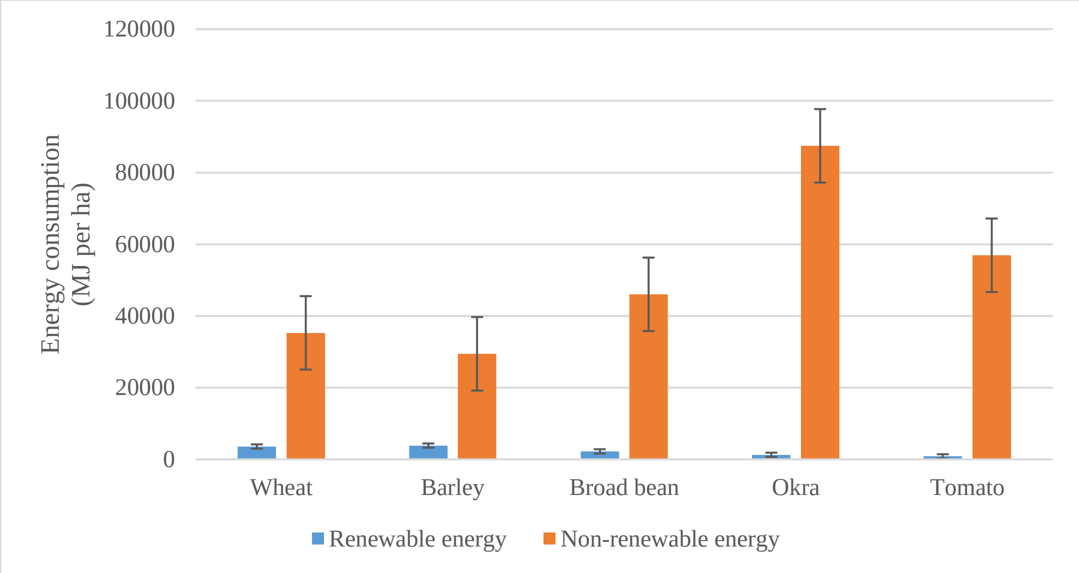

Figure 4- The distribution of energy consumption, into renewable and non-renewable energy sources

The comparison of the mass productivity of renewable energy reflects the fact that 1 MJ of renewable energy consumption can result in approximately 53 kilograms of tomato and 8 kilograms of okra, which is the highest amount among the desired crops. On the other hand, for barley and broad bean, the lowest mass productivity of renewable energy has been calculated, and 1 MJ of renewable energy consumption can only lead to the production of approximately 1 and 2.1 kilograms of barley and broad bean, respectively. Based on the obtained results, it can be concluded that the mass productivity of energy, especially non-renewable energy, for all crops is less than 1 MJ per hectare, which is consistent with the results of other studies (El-Gafy *et al*., 2017; Mirzaei *et al*., 2022). Among the examined crops, tomato has allocated the highest amount of approximately 0.78 kilograms, and broad bean has the lowest amount of approximately 0.06 kilograms of non-renewable energy mass productivity. The high mass productivity of tomato crop has been proven in the studies by El-Gafy *et al*. (2017) and Mirzaei *et al*. (2022). Finally, the results indicate that tomato and okra have the highest energy economic productivity for both types of renewable and non-renewable energy, which is consistent with the results of the study by El-Gafy *et al*. (2017).

Table 5- Values of energy component criteria in the proposed WEFE nexus

Crops	Energy consumption (MJ/he)		Energy mass productivity (Kg/MJ)		Energy economic productivity ($/MJ)	
	Renewable	Non-renewable	Renewable	Non-renewable	Renewable	Non-renewable
Wheat	3580	35280	1.35	0.137	0.366	0.037
Barley	3834	29443	1.04	0.136	0.192	0.025
Broad bean	2219	46024	1.20	0.058	0.515	0.025
Okra	1265	87454	7.68	0.111	7.270	0.105
Tomato	834	56920	53.02	0.777	9.273	0.136

Analysis of Environmental Component Criteria

The results presented in Table 6 reveal that okra and tomato exhibit the highest consumption of fertilizers and pesticides. okra is estimated to consume around 1321 kilograms, while tomato consumes approximately 1182 kilograms per hectare. As for pesticide consumption, okra utilizes about 18 liters per hectare, whereas tomato requires around 6 liters. Moreover, the findings indicate that okra and tomato production are associated with the highest levels of CO_2 emissions, approximately 4691 and 2987 kilograms per hectare, respectively. Conversely, wheat and barley production result in the lowest CO_2 emissions, approximately 1487 and 1766 kilograms per hectare, respectively. Saray *et al.* (2022) and Saray & Haghighi (2023) conducted an assessment of CO_2 emissions from wheat and barley production and discovered that these emissions were lower compared to other crops. Furthermore, Masaeli *et al.* (2023) demonstrated that barley production has the lowest CO_2 emissions. In terms of water conservation and subsequently ensuring wetland water rights, barley (approximately 6.3) and wheat (approximately 4.9) achieved the highest scores, while okra (approximately 1.2) and tomato (approximately 2.2) obtained the lowest scores (See Appendix A1). In the study conducted by Mirzaei and Zibaei (2021), which aimed to preserve the wetland, the cultivation pattern saw an increased contribution from barley, indicating its suitability in the agricultural sector for securing downstream water rights in the wetland.

Analysis of Sustainable Patterns Based on Index of WEFED Nexus

Before analyzing the TOPSIS results, the final weights of the criteria, derived from expert opinions using the FAHP method, are presented in Table 7.

Table 6- Values of environmental component criteria in the proposed WEFE nexus

Crops	Fertilizers consumption (Kg/he)	Pesticides consumption (L/he)	CO_2 emission (Kg/he)	Score of wetland conservation (1 to 9)
Wheat	847	2.58	1766	4.94
Barley	684	3.19	1487	6.27
Broad bean	750	4.67	2416	4.06
Okra	1321	17.79	4691	1.23
Tomato	1182	5.53	2987	2.19

Table 7- The importance weights of the criteria based on the FAHP method

Criteria	Weights
Water consumption	0.097
Renewable energy consumption	0.052
Non-renewable energy consumption	0.046
Water mass productivity	0.120
Renewable energy mass productivity	0.089
Non-renewable energy mass productivity	0.044
Water economic productivity	0.146
Renewable energy economic productivity	0.139
Non-renewable energy economic productivity	0.077
Fertilizers consumption	0.039
Pesticides consumption	0.037
CO_2 emission	0.061
Wetland conservation	0.054

The results of the TOPSIS closed index for different scenarios are shown in Table 8. These results indicate that tomato is given the highest priority for cultivation in scenarios WEM, EEM, WEFE, and WEFED. Following tomato, barley has the highest priority in various scenarios among the crops examined. Specifically, in scenarios WCM, ECM, and ENM, barley is given the first cultivation priority. On the other hand, okra consistently has the lowest cultivation priority among the studied crops in most scenarios, including WCM, WEM, ECM, ENM, and WEFE. Analyzing the obtained results reveals that despite its high-water consumption (ranked fourth in cultivation priority according to WCM) and relatively unfavorable environmental conditions (ranked third in cultivation priority according to ENM), tomato still has the highest cultivation priority from a holistic perspective, considering all proposed WEFE components. This is due to its ability to enhance the economic productivity of water and energy resources. Conversely, okra has a lower cultivation priority in the proposed WEFE pattern due to its poor performance in environmental criteria and its higher water and energy consumption. The sensitive analysis revealed a notable shift in the middle rankings. Specifically, when the "wetland conservation" criterion was removed, the ranking of okra increased, placing it in a higher priority position within the cropping pattern. This finding aligns perfectly with the theoretical expectation, as okra is a crop with high water consumption that was penalized in the original model due to its relatively lower score on the separate "wetland conservation" criterion. Its rise in ranking when that penalty is removed confirms that the model is logically capturing the interplay between these criteria.

Based on the findings of Table 8, it can be concluded that there is minimal disparity between the results of the WEFE and WEFED scenarios. This suggests that the sustainable pattern derived from the WEFED scenario (the importance weight of the criteria based on the opinions of regional decision-makers) is almost comparable to the sustainable pattern obtained from the WEFE scenario (equal importance weights for the criteria). Nonetheless, distinct variations exist in cultivation priorities between the proposed WEFE patterns and sustainable patterns from different perspectives. For instance, the cultivation priority outcomes of different scenarios, where environmental criteria are disregarded, differ completely from the cultivation priority outcomes based on environmental management. When factors such as fertilizer and pesticide consumption, CO_2 emissions, wetland conservation, and water and energy resource management are given greater significance, crops such as barley and wheat receive the highest cultivation priority. Conversely, when the economic productivity of water and energy resources holds greater importance, the cultivation priority is higher for tomato. Finally, the results of the sustainability criteria for each pattern are presented in Table 9.

In scenarios WCM, ECM, and ENM, despite reducing the use of water and non-renewable energy and improving environmental factors, there is a decrease in the economic productivity of water and energy compared to the current pattern. Consequently, sustainable agricultural management, which emphasizes reducing water and energy consumption and addressing environmental concerns, cannot achieve satisfactory economic efficiency. This implies that we cannot be optimistic about implementing these patterns in the region. The results also show that in scenarios WEM and EEM, there will be improvements in the mass and economic productivity of water and energy. However, we cannot expect significant improvements in environmental parameters, particularly in reducing water and energy consumption, from these perspectives.

Table 8- prioritizing crop cultivation under different scenarios

Scenarios	Wheat	Barley	Broad bean	okra	tomato
WCM	0.88	0.89	0.87	0.05	0.62
	2	1	3	5	4
WEM	0.36	0.37	0.30	0.18	0.82
	3	2	4	5	1
ECM	0.76	0.78	0.48	0.16	0.3
	2	1	3	5	4
EEM	0.22	0.23	0.19	0.5	0.87
	4	3	5	2	1
ENM	0.66	0.69	0.59	0.16	0.6
	2	1	4	5	3
WEFE	0.45	0.47	0.39	0.27	0.71
	3	2	4	5	1
WEFED	0.35	0.37	0.31	0.35	0.8
	3	2	5	4	1

The blue, green, yellow, orange, and red cells represent the first to fifth priority order of crop cultivation, respectively.

Table 9- Value of criteria under different scenarios

Criteria	Base	WCM	ECM	WEM	EEM	ENM	WEFE	WEFED
Water consumption	13347	9627	10511	15468	22225	11780	15280	17771
Renewable energy consumption	2346	2741	2915	2114	1714	2599	2277	2053
Non-renewable energy consumption	51024	41582	41500	49113	58067	44015	48735	52136
Water mass productivity	0.85	0.91	0.81	1.22	1.19	0.95	1.06	1.13
Renewable energy mass productivity	12.86	11.01	7.86	22.71	25.23	13.16	18.03	21.15
Non-renewable energy mass productivity	0.24	0.23	0.20	0.38	0.40	0.26	0.32	0.35
Water economic productivity	0.22	0.21	0.19	0.25	0.27	0.21	0.24	0.25
Renewable energy economic productivity	3.53	2.14	1.86	4.57	5.96	2.75	3.93	4.73
Non-renewable energy economic productivity	0.07	0.05	0.05	0.08	0.09	0.06	0.07	0.08
Fertilizers consumption	957	848	848	980	1083	887	956	1004
Pesticides consumption	6.75	4.08	4.51	5.53	7.93	4.74	5.75	6.51
CO_2 emission	2669	2135	2140	2560	3056	2280	2540	2729
Wetland conservation	3.74	4.50	4.62	3.62	2.89	4.26	3.78	3.44

The green and red colors of the cells indicate a better and worse situation, respectively, compared to the current pattern.

Therefore, a narrow focus on the economic aspect could potentially undermine the regional environmental conditions. The WEFE scenario demonstrates the highest number of improvements in sustainable management criteria compared to the current pattern (11 cells marked in green). Hence, considering all perspectives and giving equal importance to them in sustainable agricultural management can help achieve most sustainability goals. The positive impact of the WEFE nexus on achieving sustainable agricultural patterns has been demonstrated in various studies (Saray *et al.*, 2022; Mirzaei *et al.*, 2022; Mirzaei *et al.*, 2024b).

It is worth noting that the WEFE scenario shows an increase in water consumption compared to the current pattern. This highlights the fact that patterns aiming to reduce water consumption may not necessarily be sustainable (Sarbijan *et al.*, 2025). The results of the WEFED scenario align with those of the WEM and EEM scenarios, indicating that economic criteria hold greater importance according to the decision-makers in the studied region. Thus, in this scenario, there are improvements in the mass and economic productivity of water and energy resources compared to the current pattern, while water and energy consumption and other environmental factors face an undesirable situation.

Conclusion and Recommendations

The aim of the present study is to achieve the objectives of sustainable management in the agricultural sector by designing a comprehensive system based on decision-makers' opinions. The study focuses on the interrelationships between water, energy, food, and the environment, using the WEFE nexus concept. Sustainable patterns for the agricultural sector are derived from this nexus, taking into account decision-makers' opinions from various research areas. The study area selected for this research is the Shadegan plain in Khuzestan province, Iran. Sustainable patterns are obtained under 7 different scenarios, including water consumption management (WCM), energy consumption management (ECM), water economic management (WEM), energy economic management (EEM), environmental management (ENV), comprehensive management with equal importance to all criteria (WEFE), and comprehensive management with importance based on the opinions of regional decision-makers (WEFED). The results of the different sustainable scenarios highlight the significant role of decision-makers' and managers' perspectives in sustainable agricultural management. For example, if decision-makers' prioritize water consumption management, energy consumption, and other environmental dimensions such as chemical pollutants, CO_2 emissions, and wetland conservation, the cultivation priority will be given to barley and wheat. However, despite the improvement in environmental conditions, the economic situation of farmers will worsen compared to the current pattern in the region. On the other hand, if economic components are given greater importance, tomato cultivation becomes the first priority. Although this improves economic water and energy productivity indicators, it leads to increased consumption of water and non-renewable energy resources and environmental degradation. The WEFE scenario demonstrates that giving equal importance to all dimensions can result in simultaneous economic and environmental management. However, it is important to note that water consumption will increase compared to the current pattern in the region. This contradicts the viewpoint of most policy-makers and decision-makers who prioritize reducing water consumption for sustainable agricultural development. Decision-makers in this field need to develop suitable patterns that improve economic resource efficiency through a comprehensive and systemic approach. When these patterns result in increased water consumption, it is crucial to manage water consumption through effective water resource management policies while implementing sustainable patterns. The results of the WEFED scenario indicate that the prevailing perspective in the region aligns closely with the WCM, ECM, and ENV scenarios, with less emphasis on economic productivity components compared to resource consumption management. Based on the findings, while the WEFE scenario offers a more balanced sustainability performance, its implementation would lead to increased water consumption compared to the current pattern-a critical challenge in water-scarce regions. To enable the adoption of such sustainable cropping patterns, it is essential to complement them with water-saving strategies. These include promoting modern irrigation technologies, improving water conveyance efficiency, implementing incentive-based policies to encourage farmers to adopt water conservation practices, and Incentive programs to shift cultivation towards increased tomato production while adhering to water consumption quotas and utilizing irrigation technologies. Effective monitoring and governance mechanisms will also be crucial to ensure that sustainability objectives are met without exacerbating water scarcity.

Appendix A1: Expert Scoring Rubric for Wetland Conservation Criterion

This appendix outlines the rationale and scoring methodology for the qualitative "Wetland Conservation" criterion presented in Table 6. The scores (on a scale of 1 to 9) were assigned by a panel of regional agricultural and environmental experts based on the combined impact of two primary factors: 1) Crop Water Consumption and 2) Alignment with Environmental Water Rights.

The scoring rubric used by the experts is summarized in the table below. A higher score indicates a cropping pattern that is more compatible with the goal of preserving water for the Shadegan Wetland's ecological needs.

Table A1: Expert Scoring Rubric for Wetland Conservation

Score	Description / Justification
1-2 (Very Low)	Assigned to crops with very high-water consumption (e.g., >20,000 m³/he). Cultivation of these crops significantly reduces the water volume available for downstream environmental flow, posing a severe threat to the wetland's health and water rights.
3-4 (Low)	Applied to crops with high water consumption. These crops substantially compete with the wetland for water resources, leading to a significant negative impact on the potential for meeting its water rights.
5 (Medium)	Represents crops with moderate water consumption. Their cultivation has a discernible but moderate impact on the water available for the wetland, representing a neutral to slightly negative influence.
6-7 (High)	Assigned to crops with low to moderate water consumption. These crops are considered more compatible with wetland conservation, as their water use allows for a better balance between agricultural needs and environmental water allocation.
8-9 (Very High)	Reserved for crops with very low water consumption (e.g., <5,000 m³/he). These crops are highly favorable for wetland conservation, as they minimize competition for water resources, thereby preserving a greater share for fulfilling the wetland's environmental water rights and promoting its ecological sustainability.

Justification for the Approach: This expert-based scoring system allows for the integration of a critical qualitative environmental indicator into the quantitative WEFE nexus framework. It directly links agricultural water use decisions to their downstream ecological consequences, a relationship that is crucial for sustainable resource management but difficult to capture with purely quantitative metrics alone.

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نشریه اقتصاد و توسعه کشاورزی
https://jead.um.ac.ir

مقاله پژوهشی
جلد ۴۰، شماره ۲، تابستان ۱۴۰۵، ص. ۱۷۲-۱۵۱

تصمیم‌گیری در پیوند آب، انرژی، غذا و محیط زیست: مسیرهایی به سوی توسعه‌ی پایدار کشاورزی

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تاریخ دریافت:۱۴۰۴/۰۶/۳۰
تاریخ پذیرش:۱۴۰۴/۱۰/۰۶

چکیده

ما کوشیده‌ایم تا با ایجاد یک سیستم جامع و به‌هم‌پیوسته، تعریف تازه‌ای از پیوند آب-انرژی-غذا-محیط‌زیست-تصمیم‌گیرندگان (WEFED) ارائه دهیم. در این مطالعه، معیارهای مصرف، بهره‌وری فیزیکی و بهره‌وری اقتصادی مربوط به آب آبیاری، انرژی تجدیدپذیر و تجدیدناپذیر، همچنین معیارهای مصرف کود و آفت‌کش، انتشار CO_2 و حفاظت از تالاب‌ها را برای تبیین پیوند آب-انرژی-غذا-محیط‌زیست (WEFE) در نظر گرفتیم. سپس تأثیر دیدگاه‌های تصمیم‌گیرندگان را بر معیارهای این پیوند، در قالب هفت سناریوی مدیریتی متفاوت شامل مدیریت مصرف آب (WCM)، مدیریت مصرف انرژی (ECM)، مدیریت اقتصادی آب (WEM)، مدیریت اقتصادی انرژی (EEM)، مدیریت زیست‌محیطی (ENM)، مدیریت با وزن‌دهی مساوی به معیارها (WEFE)، و مدیریت با وزن‌دهی بر اساس نظرات تصمیم‌گیرندگان منطقه مورد مطالعه (WEFED) با استفاده از روش TOPSIS ارزیابی کردیم. به‌منظور ادغام صریح دیدگاه‌های تصمیم‌گیرندگان در این سیستم (رویکرد WEFED)، وزن اختصاص‌یافته به هر معیار پایداری در یکی از سناریوها، مستقیماً بر اساس نظرسنجی از تصمیم‌گیرندگان محلی و با استفاده از روش فرآیند تحلیل سلسله‌مراتبی فازی (FAHP) تعیین شد. یافته‌های مطالعه نشان داد که در سناریوهای WCM، ECM و ENM، کشت جو بالاترین اولویت را داشت، با این حال، علی‌رغم بهبود پارامترهای زیست‌محیطی، کاهش بهره‌وری اقتصادی آب و انرژی نسبت به الگوی فعلی مشاهده شد. در مقابل، در سناریوهای WEM و EEM، کشت گوجه‌فرنگی در اولویت قرار گرفت و علی‌رغم بدتر شدن شرایط زیست‌محیطی، بهبود بهره‌وری فیزیکی و اقتصادی آب و انرژی نسبت به الگوی فعلی نشان داده شد. اختلاف نتایج میان الگوهای سناریوی پایدار مختلف، تأثیر قابل‌توجه دیدگاه‌های تصمیم‌گیرندگان را بر مدیریت پایدار کشاورزی برجسته ساخت. در نهایت مشخص شد که سناریوی WEFE بیشترین تعداد بهبود (۱۱ مورد از ۱۳ معیار) را در معیارهای مدیریت پایدار نسبت به الگوی فعلی به همراه دارد. بنابراین، یافته‌ها نشان داد که رویکرد کل‌نگر و مبتنی بر وزن‌دهی مساوی در پیوند (WEFE)، ضمن افزایش مصرف آب، متعادل‌ترین نتایج پایداری را ارائه می‌دهد، هرچند که اجرای آن باید با حاکمیت قوی بر آب همراه باشد.

واژه‌های کلیدی: انتشار CO_2، حفاظت از تالاب‌ها، دیدگاه‌های پایداری، مدیریت اقتصادی آب و انرژی

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https://doi.org/10.22067/jead.2025.95571.1378

Journal of Agricultural Economics & Development

Homepage: https://jead.um.ac.ir

Research Article

Vol. 40, No. 2, Summer 2026, p. 173-189

Estimating Rural Household Food Demand in Iran Using the QUAIDS Model: Insights for Policy Design

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Received: 27 September 2025 Revised: 28 December 2025 Accepted: 28 April 2026 Available Online: 28 April 2026	**How to cite this article:** Shabanzadeh-Khoshrody, M. (2026). Estimating rural household food demand in Iran using the QUAIDS model: Insights for policy design. *Journal of Agricultural Economics & Development, 40*(2), 173-189. https://doi.org/10.22067/jead.2026.95667.1382

Abstract

Food security, as a key pillar of sustainable development and social welfare, is particularly sensitive to price fluctuations and income volatility in rural communities. In Iran, recent inflationary pressures and declining household purchasing power have highlighted the need for a scientific analysis of food demand patterns and the evaluation of policy interventions. This study aims to provide a policy-oriented analysis of food demand patterns among rural households in Iran and to assess the potential impacts of alternative policy interventions. Data were drawn from the 2023 Household Income and Expenditure Survey, and the Quadratic Almost Ideal Demand System (QUAIDS) was employed to estimate consumption patterns while accounting for theoretical constraints and household demographic characteristics. Eight main food groups—cereals, proteins, dairy, oils and fats, fruits and nuts, vegetables and legumes, sugar and confectionery, and spices and beverages-were analyzed. Results indicate that cereals and proteins function as necessities with low income and price elasticities, whereas vegetables and legumes exhibit more luxury-like characteristics, with consumption increasing at higher income levels. Cross-price elasticities reveal both substitution and complementarity among food groups, providing important insights for the design of pricing and fiscal policies. Demographic factors, including household size, education, and age, significantly influence consumption patterns. Welfare analyses further show that low-income rural households are the most vulnerable to rising food prices. Overall, the findings not only corroborate previous domestic and international studies but also provide new evidence on the sensitivity of food demand to income and price changes in Iran. Based on the estimated income and own-price elasticities, the findings suggest that food subsidy reforms should focus on staple goods with low income and price elasticities to protect low-income rural households, while targeted income support and price stabilization policies are more appropriate for food groups exhibiting high income and own-price responsiveness, such as vegetables and legumes. Furthermore, the presence of significant cross-price substitution effects implies that price interventions in one food group may have spillover effects on the consumption of other foods, which should be considered in policy design.

Keywords: Food demand, Food security, Price and income elasticities, QUAIDS model, Rural areas

https://doi.org/10.22067/jead.2026.95667.1382

Introduction

Food security, as one of the fundamental pillars of sustainable development, social welfare, and economic stability, has increasingly drawn the attention of researchers and policymakers over the past two decades (FAO, 2022; World Bank, 2023). This challenge is especially pressing given that, in 2022 alone, more than 735 million people worldwide experienced hunger-a majority of them in developing countries and rural areas (WFP, 2023). Global crises such as the COVID-19 pandemic, the war in Ukraine, and the impacts of climate change have further disrupted supply chains, fueled sharp increases in food prices, and limited the access of vulnerable groups to essential goods (Valera *et al.*, 2023; Dhar *et al.*, 2024).

Recent studies highlight that households across countries, particularly in developing economies, are vulnerable to price and income shocks, because they allocate a large share of their income to food purchases and face limited substitution possibilities when adjusting their consumption (Andreyeva *et al.*, 2010; Ansah *et al.*, 2022; Dhar *et al.*, 2024). Iran is no exception. Official statistics from the Statistical Center of Iran show that food price inflation reached approximately 40 percent in 2022–2023, substantially eroding households' real purchasing power. This sharp increase in food prices has been accompanied by a decline in the consumption of protein-rich and dairy products, with the adverse effects being particularly pronounced among low-income rural households (Statistical Center of Iran, 2023). Household Income and Expenditure Survey (HIES) data suggest that own-produced food accounts for a meaningful share of food consumption among rural households, indicating their reliance on home production as a coping mechanism against market price shocks. However, empirical evidence shows that existing subsidy and compensatory policies have not been sufficient to stabilize food access, particularly under high food inflation, leading to welfare losses among rural households (Falsafian *et al.*, 2024).

At both international and national levels, numerous studies have analyzed food demand patterns using the Almost Ideal Demand System (AIDS) and its quadratic extension Almost Ideal Demand System (QUAIDS). Mekonnen *et al.* (2012) applied QUAIDS to fruit consumption in the U.S., demonstrating the model's flexibility in capturing non-linear Engel relationships. Korir *et al.* (2018), using household data from Kenya, found that protein consumption is highly responsive to price fluctuations, whereas higher income promotes a more diversified diet. Ansah *et al.* (2022) further showed that, in addition to price and income effects, household characteristics such as size, head's education, and residence location significantly influence food consumption patterns. Forgenie *et al.* (2024) analyzed per capita food consumption in net food-importing developing countries, highlighting how price shocks can disproportionately affect nutrient intake among lower-income households. Most recently, Muiruri *et al.* (2025) demonstrated in Nairobi, Kenya, that staples such as cereals and bread have low price and income elasticities, while consumption of meat and dairy products is more sensitive to income changes.

Among domestic studies, Akbari *et al.* (2017) examined the food demand of urban households in Sistan and Baluchestan Province. Their findings indicated that items such as bread and cereals, milk and eggs, legumes and vegetables, sugar, and beverages are classified as necessities, while meat, oils and fats, fruits, and nuts were found to be luxury goods with higher income sensitivity. Ataie Solout & Mohammadi (2018), using time-series data from Mazandaran Province, estimated price and income elasticities of food groups and similarly identified bread, cereals, and vegetables as necessities, while meat and fruits exhibited luxury characteristics. Baghestany & Sherafatmand (2021), applying a threshold regression model, estimated supply and demand elasticities for tea in Iran and concluded that tea is a relatively inelastic commodity. Khalili Malakshah et al. (2021)

analyzed rural and urban households across Iran and found that household characteristics such as income, size, and demographic composition significantly shape food demand patterns. Specifically, rural households exhibited lower price and income elasticities for staple foods such as cereals and bread, whereas consumption of protein-rich and dairy products was more sensitive to income changes in urban households. These findings highlight the heterogeneity of consumption patterns across regions and underscore the need for a focused analysis of rural households to inform policy interventions. Falsafian *et al.* (2024) also assessed the impact of food tariff reforms on household welfare and reported that such reforms reduced welfare, particularly among low-income and rural households. In another study, Layani & Bakhshoodeh (2025) investigated the effects of rising global food prices on rural poverty and vulnerability in Iran, showing that price increases reduced welfare and heightened household vulnerability.

Taken together, international studies indicate that food demand in low-income societies is highly sensitive to changes in prices and incomes, particularly for staple foods (Andreyeva *et al.*, 2010; Korir *et al.*, 2018; Muiruri *et al*., 2025). These studies often focus on specific commodities, regions, or short-term price shocks, leaving gaps in nationwide, comprehensive analyses. In Iran, domestic studies have primarily focused on provincial or urban households and limited food groups (Akbari *et al*., 2017; Ataie Solout & Mohammadi, 2018; Khalili Malakshah *et al.*, 2021; Falsafian *et al.*, 2024), and often rely on outdated data or omit demographic heterogeneity and policy-relevant implications. By contrast, the present study provides a nationwide, up-to-date analysis of rural food demand using 2023 Household Income and Expenditure Survey data, estimates a complete QUAIDS-based demand system across major food groups, incorporates household demographic heterogeneity, and emphasizes policy implications including targeted subsidies, price stabilization, and income support.

Furthermore, although several national-level studies on food consumption in Iran exist, many of them suffer from important limitations. These include reliance on outdated data, focus on single commodities or partial food groups, and the use of reduced-form approaches that do not estimate a complete demand system consistent with economic theory. In addition, the majority of existing studies emphasize elasticity estimation without fully exploiting demand functions for policy design, such as evaluating differential price and income responses across food groups and household characteristics. As a result, there remains a need for a comprehensive, up-to-date demand system analysis that can provide policy-relevant insights into food security and welfare in rural Iran. In this context, estimating a theoretically consistent demand system is essential not only for obtaining reliable elasticity estimates but also for understanding substitution and complementarity patterns across food groups, which are critical for effective policy design. By employing the QUAIDS model and recent nationwide data, this study addresses key limitations of existing research and provides a solid empirical foundation for designing targeted subsidies, price stabilization policies, and income support programs tailored to rural households in Iran.

Accordingly, the present study employs the QUAIDS model with data from the 2023 Household Income and Expenditure Survey to provide an evidence-based picture of rural food consumption patterns in Iran. The main contribution of this study lies in providing an updated, nationwide analysis of rural food demand in Iran using 2023 Household Income and Expenditure Survey data. Unlike previous studies that often focused on specific provinces, limited food groups, or single elasticity estimation, this study simultaneously estimates a complete demand system within the QUAIDS framework, incorporates household demographic heterogeneity, and provides policy-oriented insights by examining both income and price elasticities, including substitution and complementarity effects among food groups. This approach allows for a clearer understanding of how factors such as household size, education, gender, and age structure influence food demand, and supports the design of targeted subsidies, income support, and price stabilization policies.

The main objective of this study is to provide a comprehensive, nationwide analysis of rural food demand in Iran using 2023 Household Income and Expenditure Survey data, estimating a complete QUAIDS-based demand system, incorporating household demographic heterogeneity, and highlighting policy-relevant implications. By addressing gaps in previous domestic and international studies—such as limited coverage of rural areas, outdated data, or omission of demographic and policy considerations—this research aims to contribute both to the literature and to evidence-based policy design.

Material and Methods

Household food demand has been analyzed in the literature using a range of approaches, including single-equation models, Engel curve specifications, and complete demand systems such as the Almost Ideal Demand System (AIDS). While simpler models allow for elasticity estimation, they do not adequately capture substitution and complementarity across food groups. To address these limitations, this study employs the Quadratic Almost Ideal Demand System (QUAIDS), which extends the AIDS model by allowing for nonlinear Engel curves and greater flexibility in modeling household consumption behavior, making it particularly suitable for policy-oriented analysis in heterogeneous rural settings. This approach has been extensively applied in food demand studies across developing-country contexts, including China (Zhou & Herzfeld, 2015; Chen *et al.*, 2016), Pakistan (Hayat *et al.*, 2016), and Kenya (Korir *et al.*, 2018).

Empirical evidence suggests that QUAIDS, with its nonlinear specification, can accurately describe consumer behavior compared to linear demand systems (Mekonnen *et al.*, 2012; Sola, 2013). Additionally, this approach enables meaningful comparisons between Iran and international evidence. The QUAIDS model, originally proposed by Banks *et al.* (1997), extends the Almost Ideal Demand System (AIDS) of Deaton & Muellbauer (1980) by introducing a quadratic term of log-expenditure, which adds flexibility in modeling Engel curves. This feature is especially important when analyzing heterogeneous households, where income and demographic characteristics play a crucial role. The general QUAIDS specification for the budget share of the i-th food group can be expressed as:

$$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} lnp_j + \beta_i \ln\left(\frac{X}{P}\right) + \frac{\lambda_i}{2}\left[\ln\left(\frac{X}{P}\right)\right]^2 + \epsilon_i \quad (1)$$

Where w_i denotes the expenditure share of group i, p_j is the price of group j, X is total household expenditure and P is the translog price index defined in Equation (2). The parameters $\alpha_i, \gamma_{ij}, \beta_i, \lambda_i$ are to be estimated, and ϵ_i denotes the error term. If $\lambda = 0$ the model reduces to the standard AIDS system.

$$\ln P = a_0 + \sum_{i=1}^{n} a_i\, lnp_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} lnp_i lnp_j \quad (2)$$

In order to account for household heterogeneity, demographic variables were included in the intercept term of the demand equations using the demographic translation method, as outlined by Pollak & Wales (1992) and Poi (2012). This approach enables the intercepts to adjust systematically based on household characteristics, effectively capturing demographic diversity in preferences (Pollak & Wales, 1992; Poi, 2012).

$$w_i = \alpha_{i0} + \sum_{m=1}^{M} \delta_{im} Z_m + \sum_{j=1}^{n} \gamma_{ij} lnp_j + \beta_i \ln\left(\frac{X}{P}\right) + \frac{\lambda_i}{2}\left[\ln\left(\frac{X}{P}\right)\right]^2 + \epsilon_i \quad (3)$$

where Z_m represents demographic characteristics such as household size, education, age, and gender of the household, as specified in Equation (3).

To ensure consistency with consumer demand theory, the adding-up and homogeneity restrictions are imposed following Deaton & Muellbauer (1980), and the symmetry restriction is imposed in line with standard demand theory (Pollak & Wales, 1992; Banks *et al.*, 1997).

Adding-up

$$\sum_{i=1}^{n} \alpha_i = 1\,, \quad \sum_{i=1}^{n} \beta_i = 0\,, \quad \sum_{i=1}^{n} \lambda_i = 0\,, \quad \sum_{i=1}^{n} \gamma_{ij} = 0 \; for\ all\ j \quad (4)$$

Homogeneity

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \; for\ all\ j \quad (5)$$

Symmetry

$$\gamma_{ij} = \gamma_{ji} \; for\ all\ i,j \quad (6)$$

Based on the estimated QUAIDS parameters, income elasticities as well as uncompensated (Marshallian) and compensated (Hicksian) price elasticities are computed using the standard formulas derived from demand theory. These expressions follow the original derivations in Banks *et al.* (1997) and their applied implementation as outlined in Poi (2012), and are reported in Equations (7)– (9).

$$\eta_i = 1 + \frac{\beta_i + 2\,\lambda_i \ln(\frac{X}{P})}{w_i} \quad (7)$$

$$e_{ij}^{U} = \frac{\gamma_{ij} - \beta_i\left(w_j + \lambda_i \ln\left(\frac{X}{P}\right)\right) + \lambda_i\, w_j \ln\left(\frac{X}{P}\right)^2}{w_i} \quad (8)$$

$$e_{ij}^{C} = e_{ij}^{U} + w_j \eta_i \quad (9)$$

The demand system was estimated as a set of equations using an iterated Seemingly Unrelated Regression (SUR) procedure, which accounts for contemporaneous correlation across equation error terms and improves estimation efficiency. The implementation follows the methodological framework described in Poi (2012). The following subsection describes the data source and construction of food groups used for estimating the demand system.

Data

The data used in this study were drawn from the 2023 Household Income and Expenditure Survey (HIES) conducted by the Statistical Center of Iran. The dataset provides detailed information on household food expenditures as well as demographic characteristics. After excluding missing observations, the final sample consists of 18,138 rural households. The survey contains information on approximately 230 food items. However, estimating demand equations for each item separately is practically infeasible. Therefore, in line with the standard coding system employed by the Statistical Center of Iran, individual food items were aggregated into eight main categories: (i) bread and cereals, (ii) proteins (meat, poultry, and fish), (iii) dairy products, (iv) oils and fats, (v) fruits and nuts, (vi) vegetables and legumes, (vii) sugar, sweets, and confectionery, and (viii) spices and beverages.

Results and Discussion

Characteristics of Rural Households (HIES 2023)

Table 1 presents the descriptive statistics of the 18,138 rural households included in this study. On average, households consist of 3.34 members, with the household head being 54.34 years old and having an average education level of 3.1, corresponding roughly to lower secondary education. The majority of household heads are male (≈84%). Monthly per capita income averages 117.5 million IRR, while monthly per capita food expenditure averages 35.3 million IRR, indicating that households spend a substantial share of their income on food. These statistics provide an overview of the sample and set the stage for interpreting the subsequent empirical results on food demand patterns.

Table 1- Sample characteristics of rural households (HIES 2023)

Variable	Mean	Standard deviation	Min	Max
Household size	3.34	1.52	1	16
Household age	54.34	15	15	99
Household education (1 = illiterate; 2 = primary; 3 = lower secondary ;4= upper secondary/pre-university; 5 = associate; 6 = bachelor's ;7= master's; 8 = PhD+)	3.1	2.8	1	8
Gender (1 = male; 2 = female)	1.16	0.37	1	2
Monthly per capita income (million IRR/person)	117.5	143.7	5	1324.2
Monthly per capita food expenditure million IRR/person)	35.3	26.3	5	835.6

Estimation of the QUAIDS Model

Before estimating, the theoretical restrictions of the demand system- adding-up, homogeneity, and symmetry - were tested and imposed. The results confirmed that these conditions were not violated, ensuring the reliability of the final estimates. Moreover, a likelihood ratio (LR) test was conducted to assess the significance of the quadratic income term in the QUAIDS specification. A likelihood ratio (LR) test supported the inclusion of the quadratic income term, providing empirical justification for the use of the QUAIDS specification rather than the standard linear AIDS model. Therefore, the QUAIDS model was retained for the subsequent analysis of food demand among rural households in Iran.

Table 2 reports the estimated QUAIDS parameters for the eight food groups considered in this study. The expenditure coefficients (β), quadratic expenditure terms (λ), and cross-price parameters (γ) provide insights into the expenditure responsiveness, nonlinear demand behavior, and substitution or complementarity relationships among food groups.

The expenditure coefficients (β) highlight the responsiveness of budget shares to changes in total food expenditure. The negative and significant β for proteins implies that their budget share decreases as total expenditure rises, suggesting that rural households treat proteins as necessities. In contrast, vegetables and legumes show a positive and significant β, indicating luxury-type behavior at higher expenditure levels. This finding is consistent with Seale *et al.* (2003), who observed that dietary diversification toward vegetables increases with income growth in developing countries.

The quadratic terms (λ) capture nonlinear expenditure effects and allow Engel curves to deviate from the linear form imposed by the AIDS model. In this study, a positive and significant λ for cereals and proteins indicates that their budget shares increase at an accelerating rate as total household expenditure rises, reflecting convex Engel curves and highlighting the essential nature of these food groups. In contrast, negative and significant λ for oils and vegetables suggest that their budget shares increase at a decreasing rate or even decline at higher expenditure levels, indicating saturation effects. These results further confirm the relevance of accounting for nonlinear Engel curves in rural food demand analysis. Similar nonlinear effects have been reported in QUAIDS applications for developing-country contexts. For example, Korir *et al.* (2018) report non-linear Engel relationships in Kenya, and Ansah *et al.* (2022) apply QUAIDS in a Sub-Saharan Africa context and show that quadratic income terms help capture household heterogeneity.

Finally, the cross-price parameters (γ) reveal substitution and complementarity among food groups. For instance, cereals and proteins exhibit a positive and significant relationship, indicating substitution, while proteins and oils, as well as fruits and oils, show negative and significant coefficients, reflecting complementarity. Dairy and vegetables, on the other hand, appear to be substitutes.

These results resonate with Zhou & Herzfeld (2015) for urban China, who document substitution and complementarity patterns in a dynamic demand framework. Cross-country analyses such as Forgenie *et al.* (2024) document heterogeneous per-capita consumption patterns across net food-importing developing countries, but do not directly estimate cross-price elasticities; therefore, cite Forgenie for cross-country patterning rather than as direct evidence of substitution/complementarity.

The estimated coefficients indicate that rural Iranian households consider proteins and cereals as necessities, while vegetables and legumes exhibit luxury-like characteristics, reflecting specific local consumption patterns. Additionally, the cross-price effects reveal notable substitution and complementarity relationships, such as between cereals and proteins or oils and fruits, which have not been explicitly documented in prior studies on rural Iran. These insights provide practical guidance for designing targeted price and subsidy interventions to improve rural dietary outcomes.

Effects of Demographic Characteristics on Food Budget Shares

Table 3 presents the effects of demographic characteristics on the budget shares of different food groups in rural Iran. The results suggest that the impacts of these variables are heterogeneous across food categories, with both the sign and magnitude of the coefficients varying by commodity groups. Coefficients in Table 3 represent the marginal effect of a one-unit change in each demographic variable on the corresponding food budget share. Although numerically small due to variable scaling, these effects are statistically significant, reflecting precise estimation enabled by the large sample size.

It should be noted that conventional goodness-of-fit measures such as R^2 or RMSE are not reported for individual equations, as they are less informative in the context of QUAIDS demand systems estimated jointly under adding-up constraints. Model reliability is assessed via system log-likelihood and the statistical significance of coefficients. Potential heteroskedasticity and cross-equation correlations are accounted for through the SUR estimation procedure, following standard practice in the literature.

Household size tends to increase the budget share of dairy, oils, vegetables, and legumes, indicating that larger households allocate relatively more of their food budget to these groups. This pattern is consistent with evidence from developing-country demand studies, where larger households face tighter per capita budget constraints that lead to relatively lower budget shares for higher-cost food groups (Andreyeva *et al*., 2010; Seale *et al.*, 2003). The estimated coefficients for demographic characteristics are numerically small because they represent the marginal effect of a one-unit change in the demographic variable on food budget shares. Despite their small magnitude, these effects are statistically significant due to the large sample size, which provides high statistical power. Therefore, the results reflect realistic incremental effects in the population rather than spurious significance. Moreover, demand analysis literature highlights the role of demographic structure - such as household size - in shaping consumption patterns through economies of scale and intra-household allocation (Pollak & Wales, 1992; Casado *et al.*, 2024). Recent QUAIDS-based evidence from rural Asia also shows that food demand shifts toward staple or lower-cost items as household size increases (Phetcharat & Chinnakum, 2022). These findings suggest that budget constraints and demographic factors help explain the observed negative relationship between household size and budget shares for certain food groups.

Table 2- Estimated QUAIDS coefficients for rural households in Iran

Coefficient	Bread & Cereals	Proteins	Dairy products	Oils & fats	Fruits & nuts	Vegetables & legumes	Sugar, sweets, and confectionery	Spices & beverages
α	0.044 (0.037)	0.189* (0.048)	0.196* (0.018)	0.161* (0.019)	0.119* (0.024)	0.152* (0.023)	0.068* (0.019)	0.071* (0.015)
β	0.016 (0.015)	−0.050* (0.018)	−0.011 (0.007)	0.000 (0.007)	0.001 (0.009)	0.042* (0.008)	−0.001 (0.007)	0.003 (0.007)
λ	0.006* (0.002)	0.006* (0.002)	−0.001 (0.001)	−0.003* (0.001)	0.002*** (0.001)	−0.007* (0.001)	−0.001 (0.001)	−0.003* (0.001)
γ_1	0.026** (0.012)							
γ_2	−0.078* (0.012)	0.095* (0.022)						
γ_3	0.018* (0.005)	−0.014*** (0.007)	0.004 (0.005)					
γ_4	0.088* (0.006)	−0.018*** (0.010)	0.012** (0.005)	0.066* (0.010)				
γ_5	−0.021* (0.007)	0.016*** (0.010)	−0.011** (0.005)	−0.102* (0.007)	0.095* (0.010)			
γ_6	−0.046* (0.006)	−0.018*** (0.009)	0.028* (0.005)	−0.009 (0.006)	0.025* (0.007)	0.053* (0.008)		
γ_7	0.013** (0.006)	0.023* (0.008)	−0.022* (0.005)	−0.034* (0.007)	−0.008 (0.006)	−0.031* (0.006)	0.076* (0.009)	
γ_8	0.000 (0.005)	−0.005 (0.007)	−0.014* (0.003)	−0.002 (0.005)	0.006 (0.005)	−0.002 (0.004)	−0.017* (0.005)	0.040* (0.005)

Notes: Standard errors are reported in parentheses. Coefficients represent the estimated effect of explanatory variables on household budget shares for each food group. Asterisks denote the level of statistical significance (*: $p < 0.01$, **: $p < 0.05$).

Education is associated with lower shares for bread and cereals and oils, while it significantly increases the shares of proteins and fruits and nuts. This finding is consistent with the literature (e.g., Ogundari & Abdulai, 2013), which shows that education improves nutritional awareness and shifts consumption away from inexpensive, carbohydrate-rich, or high-fat foods toward more diverse and healthier products. Thus, education plays a crucial role in dietary upgrading in rural areas.

Gender effects are statistically significant only for bread and cereals (positive) and proteins (negative), suggesting that households with different gender compositions may vary in their allocation to staple foods. However, no significant gender differences were observed for most food groups, implying that gender per se is less influential compared to structural and economic factors in shaping rural food demand.

Age is positively associated with bread but negatively related to dairy and proteins. This pattern indicates that older households tend to maintain traditional diets centered around bread, while reducing consumption of protein-rich and dairy products, possibly due to health considerations or life-cycle changes in preferences.

Overall, the findings highlight the heterogeneous role of demographic factors in shaping food demand. Household size tends to reduce the budget share of costly or traditional goods while increasing that of cheaper or more adaptable foods. Education fosters a shift toward higher-value and nutritionally superior items. Gender effects are limited to core staples, whereas age reflects life-cycle consumption adjustments. These results align with studies from other developing countries, underscoring the importance of incorporating demographic heterogeneity into food policy design aimed at improving nutrition and food security in rural Iran.

Expenditure Elasticities of Food Groups

Table 4 presents the expenditure elasticities of major food groups in rural Iran. The findings suggest that most food groups have elasticities close to unity, indicating that food items in rural households are considered essential. In other words, even when income falls, households strive to maintain consumption of basic food items.

It should be noted that expenditure elasticities for staples such as bread and cereals (1.086) and oils (1.005) slightly exceed unity. This reflects both quantity and quality upgrading as household total food expenditure increases, and these estimates are derived using real expenditure and normalized budget shares within the QUAIDS framework. Such magnitudes are consistent with prior evidence from rural settings and are plausible within the QUAIDS framework. However, there is some variation among commodity groups. Vegetables and legumes have the highest expenditure elasticity 1.29, categorizing them as luxury goods. Although this classification is consistent with observed dietary diversification in Iran, in many developing countries vegetables are typically categorized as necessities, suggesting that local dietary preferences and price structures strongly shape this pattern. This means that as income increases, households allocate more of their budget to fresh and diverse food items like vegetables, beans, and pulses. Meat, poultry, fish, and eggs (proteins) and dairy products show elasticities below one (0.82 and 0.87, respectively), confirming their role as core necessities in rural diets. Oils and fats and fruits and nuts both have elasticities of exactly 1.00, lying on the boundary between necessities and luxuries. Sugar, sweets, and confectionery (0.99) have a virtually unitary elasticity, while spices and beverages (0.71) are the least affected by income changes due to their small and stable budget share.

Table 3- Effects of demographic characteristics on food budget shares in rural Iran

Variable	Bread & cereals	Proteins	Dairy products	Oils & fats	Fruits & nuts	Vegetables & legumes	Sugar, sweets, and confectionery	Spices & beverages
Household size	-0.001^{***} (0.000)	-0.004^{*} (0.001)	0.002^{*} (0.000)	0.004^{*} (0.000)	-0.006^{*} (0.000)	0.003^{*} (0.000)	0.001^{*} (0.000)	0.001 (0.001)
Household education (1 = illiterate; 2 = primary; 3 = lower secondary ;4= upper secondary/pre-university; 5 = associate; 6 = bachelor's ;7= master's; 8 = PhD+)	-0.006^{*} (0.000)	0.008^{*} (0.001)	0.000 (0.000)	-0.003^{*} (0.000)	0.004^{*} (0.000)	-0.002^{*} (0.000)	0.001^{*} (0.000)	-0.001^{***} (0.000)
Gender (1 = male; 2 = female)	0.017^{*} (0.003)	-0.015^{*} (0.004)	−0.002 (0.001)	−0.002 (0.001)	0.002 (0.002)	0.002 (0.002)	0.000 (0.001)	-0.002^{*} (0.001)
Household age	-0.001^{*} (0.000)	0.001^{**} (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000^{*} (0.000)	0.000^{*} (0.000)	0.000^{*} (0.000)

Notes: Standard errors are reported in parentheses. Coefficients represent the estimated effect of demographic characteristics on household budget shares for each food group. Asterisks denote the level of statistical significance (*: $p < 0.01$, **: $p < 0.05$, ***: $p < 0.10$).

These results align with findings from other developing countries. Seale *et al*. (2003) found that most food groups in low- and middle-income countries are considered necessities with income elasticities close to one. Similarly, Kumar *et al*. (2011) estimated demand elasticities for food commodities in India and reported that cereals and other staples behave as necessities, while higher-value items such as fruits and animal products exhibit higher elasticities. Studies in countries like Kenya by Muiruri *et al*. (2025) show that staples like proteins and dairy are essential, while vegetables and fruits have higher elasticities, behaving more like luxury goods - similar to the trend observed in Iran. Mekonnen *et al*. (2012) applied QUAIDS to fruit consumption in the U.S., showing the flexibility of the model in capturing Engel curve non-linearities. In Sub-Saharan Africa, similar results are reported by Ansah *et al*. (2022) and Korir *et al*. (2018), where staple foods dominate household consumption, but as income rises, the consumption of higher-quality and more diverse items increases.

Overall, the expenditure elasticity results suggest that rural Iranian households view staple foods as necessities, but as incomes increase, there is a shift towards consuming more nutrient-rich and higher-quality foods, particularly vegetables and legumes. These findings imply that rural households prioritize staple foods but increase consumption of nutrient-rich items like vegetables and legumes as income rises. For policymakers, this suggests that income-support programs, targeted subsidies, or nutrition education initiatives can effectively encourage healthier diets. Specifically, policies could focus on increasing affordability and accessibility of vegetables and legumes, while maintaining support for staple foods to ensure food security. Additionally, complementary measures such as price incentives or awareness campaigns can guide households toward more balanced and diverse dietary choices, aligning with broader rural nutrition and health objectives.

Table 4- Expenditure elasticities of food groups in rural Iran

Food group	Bread & cereals	Proteins	Dairy products	Oils & fats	Fruits & nuts	Vegetables & legumes	Sugar, sweets, and confectionery	Spices & beverages
Expenditure elasticity	1.086* (0.082)	0.819* (0.064)	0.874* (0.079)	1.005* (0.076)	1.014* (0.088)	1.286* (0.058)	0.989* (0.078)	0.706* (0.021)

Notes: Standard errors are reported in parentheses. Expenditure elasticities represent the responsiveness of household budget shares to changes in total food expenditure for each food group. Asterisks denote the level of statistical significance (*: $p < 0.01$).

Price Elasticities of Food Groups

Before discussing the elasticity results, it is important to clarify that the γ parameters reported in Table 1 are QUAIDS price coefficients rather than price elasticities. All own-price and cross-price elasticities are derived from these coefficients using standard QUAIDS formulas and are reported separately in Tables 5 (Marshallian) and 6 (Hicksian). Note that due to numerical approximations in deriving elasticities from estimated QUAIDS coefficients, cross-price elasticities may slightly violate symmetry (e.g., elasticity of cereals w.r.t. proteins ≠ elasticity of proteins w.r.t. cereals). These minor deviations do not affect the overall interpretation of substitution and complementarity patterns among food groups. The estimated uncompensated (Marshallian) and compensated (Hicksian) price elasticities for food groups in rural Iran reveal patterns largely consistent with theoretical expectations and international evidence. For bread and cereals, the Marshallian price elasticity is approximately -0.87, with the Hicksian elasticity slightly higher in absolute value. This indicates that price changes have limited impact on consumption, as bread and cereals are staple and essential items in rural households. Similar results have been documented in Iran and other developing countries (Falsafian *et al*., 2024; Muiruri *et al*., 2025). From a policy perspective, evidence from rural China (Wang *et al.*, 2025) suggests that subsidies and support programs should prioritize staple foods to protect vulnerable households from the adverse effects of price fluctuations.

In contrast, spices and beverages show relatively low own-price elasticities (Marshallian ≈ -0.20; Hicksian ≈ -0.45), reflecting their small and stable budget share in rural households. Income effects on demand are minimal and consumers exhibit limited response to price changes for this group. Similar findings have also been reported in domestic studies, such as Khalili Malakshah *et al.* (2021), which estimate QUAIDS for Iranian rural and urban households and report patterns consistent with modest price responsiveness for several small-budget categories.

However, this pattern differs from some studies in South Asia and Africa that report higher price responsiveness for similar items (Andreyeva *et al.*, 2010; Muiruri *et al.*, 2025), underscoring the importance of context-specific consumption habits.

Animal-based products, such as dairy, show relatively high price elasticities (-0.946 Marshallian; -0.957 Hicksian), indicating that price increases can noticeably reduce consumption, although elasticities remain below unity in absolute terms. This pattern aligns with international evidence showing that animal-sourced foods are typically more price-sensitive than staple foods (Andreyeva *et al.*, 2010). Policy implications include the need for targeted support, such as subsidies or income-based assistance, to protect low-income rural households from reductions in protein consumption.

Cross-price elasticities reveal additional insights. While some cross-price elasticities appear relatively large in magnitude, such values are not uncommon in rural and low-income settings, where households face tight budget constraints and limited substitution possibilities within narrowly defined consumption baskets. Negative relationships between the prices of spices/beverages and sugar, confectionery, or dairy indicate complementarity-for example, tea and beverages are often consumed with sweets or dairy products. These patterns are consistent with empirical evidence from Iran (Falsafian *et al.*, 2024) and suggest policy options such as taxation on sugary drinks, which could indirectly reduce sugar and confectionery consumption (Andreyeva *et al.*, 2010). Conversely, positive cross-price elasticities between spices/beverages and fruits/nuts suggest substitution, implying that households may shift toward healthier alternatives when prices rise, a trend also observed in other Asian contexts (Muiruri *et al.*, 2025).

Overall, our elasticity estimates broadly align with international evidence: staple foods (cereals and proteins) are relatively price-inelastic, animal-sourced products tend to be more price-sensitive, and vegetables show higher income responsiveness (Seale *et al.*, 2003; Andreyeva *et al.*, 2010). Nevertheless, two empirical patterns deserve cautious interpretation. First, spices and beverages exhibit relatively low own-price elasticities in our rural sample (Marshallian ≈ −0.20; Hicksian ≈ −0.45), which contrasts with some studies reporting higher sensitivities for similar items. This discrepancy is plausibly explained by a combination of factors: cultural consumption patterns in Iran (e.g., habitual tea consumption that is relatively inelastic), the very small budget share and frequent purchase frequency of these items (which can dampen measured elasticities), and aggregation/price-measurement issues (grouping heterogeneous subitems or using area-level price proxies can bias elasticities toward zero). Second, the modest responsiveness observed for sugar and confectionery may partly reflect their complementarity with beverages (consumed together), household-level home production or transfers, and the particular way these items are grouped in the HIES data rather than true insensitivity to price. Taken together, these caveats affect the interpretation of specific cross-price relationships but do not alter the overall validity of the estimated demand system or the main policy-relevant conclusions.

The differences between Marshallian and

Hicksian elasticities are generally small but meaningful. For essential goods like cereals, Marshallian elasticities are slightly lower due to income effects reducing consumption, while for items with small budget shares, the differences are negligible. These results are consistent with theoretical predictions and evidence from developing countries (Falsafian *et al.*, 2024; Muiruri *et al.*, 2025).

In conclusion, the findings indicate that policy interventions should prioritize staple and high-consumption foods to ensure food security among low-income rural households. Price and expenditure elasticities suggest that targeted subsidies for cereals, proteins, and dairy products can effectively stabilize consumption of essential items. Additionally, the observed substitution and complementarity patterns among food groups provide actionable guidance for designing taxes, incentives, or educational campaigns to encourage healthier dietary choices. By explicitly linking elasticity estimates to policy instruments, our study demonstrates how demand analysis can inform evidence-based interventions in rural Iran.

Conclusion and Policy Implications

This study employed the QUAIDS model and the 2023 Household Income and Expenditure Survey (HIES) data to analyze rural food demand in Iran. The findings indicate that household consumption patterns are strongly influenced by income levels, relative prices, and demographic characteristics. Staple foods, such as cereals and proteins, are identified as necessities with low income and price elasticities, whereas vegetables and legumes exhibit more luxury-like behavior, with consumption rising at higher income levels. Cross-price elasticities reveal clear substitutive and complementary relationships among food groups, providing direct guidance for policy design. For example, modest taxes on sugary beverages can reduce consumption of both beverages and complementary sweets, while targeted support for staples like cereals, proteins, and dairy products can protect rural households from welfare losses due to price fluctuations.

Table 5– Uncompensated (Marshallian) price elasticities of food groups in rural Iran

Food group	Bread & cereals	Proteins	Dairy products	Oils & fats	Fruits & nuts	Vegetables & legumes	Sugar, sweets, and confectionery	Spices & beverages
Bread & Cereals	−0.873* (0.068)	−0.249* (0.044)	0.232* (0.059)	0.967* (0.063)	−0.205* (0.068)	−0.366* (0.044)	0.145** (0.064)	−0.004 (0.005)
Proteins	−0.452* (0.070)	−0.608* (0.080)	−0.128 (0.086)	−0.202*** (0.113)	0.150 (0.098)	−0.203* (0.066)	0.262* (0.100)	−0.005 (0.007)
Dairy Products	0.093* (0.029)	−0.035 (0.027)	−0.946* (0.060)	0.127** (0.054)	−0.111** (0.053)	0.167* (0.032)	−0.250* (0.052)	−0.151* (0.042)
Oils & Fats	0.471* (0.032)	−0.049 (0.037)	0.143** (0.056)	−0.273** (0.113)	−0.985* (0.069)	−0.090** (0.043)	−0.382* (0.078)	−0.022 (0.045)
Fruits & Nuts	−0.123* (0.038)	0.076** (0.036)	−0.116*** (0.062)	−1.123* (0.079)	−0.077 (0.096)	0.144* (0.046)	−0.094 (0.073)	0.057 (0.051)
Vegetables & Legumes	−0.263* (0.036)	−0.038 (0.034)	0.338* (0.054)	−0.104 (0.069)	0.243* (0.065)	−0.680* (0.056)	−0.349* (0.068)	−0.035 (0.031)
Sugar, Sweets, and Confectionery	0.061** (0.031)	0.098* (0.031)	−0.241* (0.052)	−0.372* (0.075)	−0.082 (0.062)	−0.236* (0.041)	−0.131 (0.097)	−0.193* (0.052)
Spices & Beverages	−0.004 (0.026)	−0.004 (0.025)	−0.151* (0.040)	−0.024 (0.052)	0.054 (0.047)	−0.035 (0.030)	−0.189* (0.053)	−0.207* (0.057)

Notes: Standard errors are reported in parentheses. Elasticities represent the responsiveness of household budget shares to changes in the prices of each food group. Asterisks denote the level of statistical significance (*: $p < 0.01$, **: $p < 0.05$, ***: $p < 0.10$).

Table 6– Compensated (Hicksian) price elasticities of food groups in rural Iran

Food group	Bread & cereals	Proteins	Dairy products	Oils & fats	Fruits & nuts	Vegetables & legumes	Sugar, sweets, and confectionery	Spices & beverages
Bread & Cereals	–0.857* (0.067)	–0.282* (0.043)	0.209* (0.058)	0.967* (0.062)	–0.203* (0.066)	–0.314* (0.043)	0.143** (0.063)	–0.002 (0.045)
Proteins	–0.428* (0.066)	–0.658* (0.078)	–0.163*** (0.083)	–0.200*** (0.111)	0.154*** (0.095)	–0.123*** (0.063)	0.259* (0.097)	–0.018 (0.087)
Dairy Products	0.100* (0.028)	–0.051*** (0.026)	–0.957* (0.060)	0.127** (0.053)	–0.110** (0.052)	0.192* (0.032)	–0.251* (0.051)	–0.160* (0.042)
Oils & Fats	0.479* (0.031)	–0.065*** (0.036)	0.132** (0.055)	–0.273** (0.113)	–0.984* (0.069)	–0.064 (0.042)	–0.383* (0.077)	–0.022 (0.054)
Fruits & Nuts	–0.114* (0.037)	0.057*** (0.035)	–0.129** (0.061)	–1.123* (0.079)	–0.075 (0.095)	0.173* (0.045)	–0.095 (0.072)	0.058 (0.042)
Vegetables & Legumes	–0.250* (0.034)	–0.065*** (0.033)	0.320* (0.053)	–0.103 (0.068)	0.245* (0.064)	–0.639* (0.055)	–0.351* (0.067)	–0.014 (0.087)
Sugar, Sweets, and Confectionery	0.069** (0.030)	0.082* (0.031)	–0.252* (0.052)	–0.372* (0.075)	–0.081 (0.061)	–0.211* (0.040)	–0.132 (0.097)	–0.194* (0.074)
Spices & Beverages	0.002 (0.025)	–0.017 (0.024)	–0.160* (0.039)	–0.024 (0.052)	0.055 (0.046)	–0.015 (0.029)	–0.190* (0.053)	–0.450* (0.034)

Notes: Standard errors are reported in parentheses. Elasticities represent the responsiveness of household budget shares to price changes, holding utility constant. Asterisks denote the level of statistical significance (*: $p < 0.01$, **: $p < 0.05$, ***: $p < 0.10$).

Demographic factors further contribute to heterogeneous consumption patterns. Household size and age influence dietary allocation, while higher educational attainment is associated with shifts toward healthier and more diversified diets. These results suggest that nutrition education programs can effectively complement fiscal and pricing measures to enhance food security in rural areas. Analysis of both uncompensated (Marshallian) and compensated (Hicksian) price elasticities shows that animal-based products are relatively price-sensitive, indicating that low-income households may face reductions in protein consumption without targeted interventions. In contrast, spices and beverages exhibit very low own-price elasticities, reflecting small budget shares and culturally ingrained consumption habits. These patterns underscore the importance of interpreting elasticity results within the context of local dietary practices.

Based on these findings, rural food policy in Iran should adopt a multidimensional approach that considers both the price sensitivity of different food groups and household heterogeneity. Broad subsidies are being phased out, so targeted mechanisms—such as conditional transfers, vouchers, or local price stabilization programs—can help vulnerable households access essential items during periods of price volatility. Support for price-elastic products like dairy and proteins can be implemented through temporary programs coordinated by local authorities. Nutrition education and outreach initiatives can improve diet quality, while promoting household-level food production can further enhance food security and complement fiscal measures. Policy interventions should also consider demographic characteristics, including household size, age, and education, to ensure that programs reach those most affected by dietary constraints.

While this study provides valuable insights into rural food demand and policy implications in Iran, it has some limitations. The analysis relies on cross-sectional HIES data, which may not fully capture temporal dynamics or seasonal variations in consumption and prices. Additionally, price data are based on aggregated regional averages, which could mask local heterogeneity. Future research could address these limitations by employing time-series data, finer geographic disaggregation, or more detailed price and quantity measures to refine demand elasticity estimates and strengthen policy guidance.

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مقاله پژوهشی

جلد ۴۰، شماره ۲، تابستان ۱٤۰۵، ص. ۱۸۹-۱۷۳

برآورد تقاضای مواد غذایی خانوارهای روستایی در ایران در چارچوب مدل QUAID: شواهدی برای طراحی سیاست‌ها

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تاریخ دریافت:۱۴۰۴/۰۷/۰۵
تاریخ پذیرش:۱۴۰۵/۰۲/۰۸

چکیده

امنیت غذایی به‌عنوان یکی از مهم‌ترین ارکان توسعه پایدار و رفاه اجتماعی، به‌ویژه در جوامع روستایی، همواره تحت‌تأثیر تغییرات قیمتی و نوسانات درآمدی قرار دارد. در ایران، فشارهای تورمی سال‌های اخیر و کاهش قدرت خرید خانوارها، ضرورت تحلیل علمی الگوی تقاضای مواد غذایی و ارزیابی پیامدهای سیاست‌های حمایتی را بیش از پیش آشکار ساخته است. این پژوهش با هدف تحلیل سیاستی تقاضای مواد غذایی در مناطق روستایی ایران انجام شد. داده‌های مورد استفاده از پیمایش هزینه و درآمد خانوار سال ۱۴۰۲ استخراج گردید و برای برآورد الگوهای مصرفی، سیستم تقاضای QUAIDS با اعمال محدودیت‌های نظری و در نظر گرفتن متغیرهای جمعیت‌شناختی به‌کار گرفته شد. هشت گروه اصلی غذایی شامل غلات، پروتئین‌ها، لبنیات، روغن‌ها و چربی‌ها، میوه و خشکبار، سبزیجات و حبوبات، قند و شیرینی، و ادویه و نوشیدنی‌ها مورد بررسی قرار گرفتند. نتایج نشان داد که غلات و پروتئین‌ها در مناطق روستایی ایران ماهیت ضروری دارند و کشش‌های درآمدی و قیمتی آن‌ها پایین است، در حالی‌که گروه‌هایی مانند سبزیجات و حبوبات بیشتر به‌عنوان کالاهای لوکس عمل می‌کنند. بررسی کشش‌های قیمتی متقاطع بیانگر وجود روابط جانشینی و مکملی بین گروه‌های غذایی بود که در طراحی سیاست‌های قیمتی و مالیاتی اهمیت دارد. همچنین، متغیرهای جمعیت‌شناختی از جمله اندازه خانوار، تحصیلات و سن، تأثیر معناداری بر الگوی مصرف داشتند. یافته‌های پژوهش علاوه بر تأیید نتایج مطالعات مشابه داخلی و بین‌المللی، با ارائه شواهدی جدید در زمینه حساسیت تقاضای مواد غذایی به تغییرات درآمدی و قیمتی در ایران، بر ضرورت تدوین سیاست‌های چندبعدی در حوزه امنیت غذایی تأکید دارد. بر این اساس، بازنگری در یارانه‌های غذایی، طراحی حمایت‌های هدفمند برای کالاهای پرکشش، ارتقای آگاهی تغذیه‌ای، و توجه به ناهمگنی جمعیتی می‌تواند به بهبود رفاه و امنیت غذایی خانوارهای روستایی کشور کمک کند.

واژه‌های کلیدی: امنیت غذایی، تقاضای مواد غذایی، کشش قیمتی و درآمدی، مدل QUAIDS، مناطق روستایی

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https://doi.org/10.22067/jead.2026.95667.1382

Journal of Agricultural Economics & Development

Homepage: https://jead.um.ac.ir

Research Article
Vol. 40, No. 2, Summer 2026, p. 191-209

The Impact of Structural and Behavioral Shocks on Market Power in Iran's Food Industry

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Received: 04 November 2025 Revised: 25 January 2026 Accepted: 27 April 2026 Available Online: 27 April 2026	**How to cite this article:** Dindar Rostami, M., Ranjbaraki, A., & Motalebi, M.M. (2026). The impact of structural and behavioral shocks on market power in Iran's food industry. *Journal of Agricultural Economics & Development, 40*(2), 191-209. https://doi.org/10.22067/jead.2026.96326.1399

Abstract

This study investigates the effects of structural and behavioral shocks on market power across 17 four-digit ISIC subsectors of Iran's food industry from 2002 to 2022. We employ a Panel Structural Vector Autoregression (PSVAR) model within the Structure-Conduct-Performance (SCP) framework, enabling a dynamic analysis of the interactions between structural and behavioral shocks. The variables examined include the exchange rate, energy costs, market concentration, value added, advertising expenditures, and intermediate input costs. Variance decomposition results reveal that structural and cost-related factors—intermediate input costs, value added, energy, and the exchange rate—account for over 80% of the variation in market power (Lerner index). Intermediate input costs emerge as the most significant negative driver of market power. Market concentration exerts a positive effect, while value added has a reinforcing effect through innovation. In contrast, behavioral factors such as advertising play a purely marginal role, contributing less than 1%. Owing to institutional constraints and consumer price sensitivity, these factors fail to significantly influence firms' pricing power. These findings confirm that market power in Iran's food industry is primarily shaped by cost structure, industrial concentration, and macroeconomic policies rather than by firms' behavioral strategies. Accordingly, given the key role of structural and cost factors, policy recommendations include managing production costs, fostering innovation and value added, mitigating exchange rate risk, regulating market structure, rethinking advertising strategies, and strengthening market regulation policies.

Keywords: Iran, Food industries, Lerner index, Market power, Panel SVAR, SCP framework

https://doi.org/10.22067/jead.2026.96326.1399

Introduction

The food industry is a cornerstone of economic stability and social welfare, playing a vital role in ensuring food security, generating employment, and contributing to gross domestic product. Beyond meeting nutritional and public health needs, this industry is particularly vulnerable to external shocks—such as climate change and geopolitical tensions—making resilience and innovation essential (Wang *et al.*, 2025). Technological advances, including mechanization and biotechnology, have enhanced productivity and sustainability while simultaneously shaping market power dynamics (Wang *et al.*, 2025).

Iran's food industry, however, faces considerable structural and external challenges. High market concentration in certain subsectors—such as bread and beverage production—coupled with volatile exchange rates, rising energy costs (despite subsidies), and heavy reliance on imported intermediate inputs, has undermined pricing stability and weakened firm competitiveness (Khodadkashi *et al.*, 2018; Akhani *et al.*, 2024). These conditions distort market power and may lead to higher consumer prices, lower productivity, and increased food insecurity.

Market power refers to a firm's ability to set prices above marginal cost or to pressure suppliers into accepting lower prices. The Structure-Conduct-Performance (SCP) framework serves as a key theoretical lens, linking market structure (e.g., concentration, entry barriers) to firm conduct (e.g., pricing strategies, advertising), and ultimately to market performance (e.g., profitability, productivity). The core premise is that market structure shapes conduct, which in turn determines performance (Mydland *et al.*, 2022).

Previous research on market power in the food industry falls broadly into two streams. International studies have largely emphasized behavioral factors such as advertising and branding (Apelbaum, 1999; Tripathy, 2025), the relationship between innovation, productivity, and markups (Jaumandreu & Lopez, 2024; Wang *et al.*, 2025), and the role of market structure and globalization in shaping profit margins (Syverson, 2019). Domestic Iranian studies, in contrast, have focused on foreign competition (Shahiki Tash & Ettazii, 2012), measuring monopoly power and its dispersion across the industry (Khodadkashi *et al.*, 2015, Khodadkashi *et al.*, 2018; Heydari, 2019), and the effects of macroeconomic policies such as energy subsidies (Akhani *et al.*, 2024). While valuable, these studies leave a clear gap: first, a lack of dynamic, shock-based analysis that captures the causal and intertemporal interactions between structural factors (costs, concentration) and behavioral factors (advertising) within the SCP framework. Second, few studies have adopted a structural, dynamic modeling approach tailored to the unique features of Iran's economy—namely, energy subsidies, exchange rate volatility, and a concentrated market structure.

This study aims to fill that gap through both methodological and substantive innovation. Methodologically, it introduces, for the first time in the Iranian context, a Panel Structural Vector Autoregression (PSVAR) model. This approach enables a dynamic, simultaneous analysis of shocks to key variables, identification of causal relationships, separation of short- from long-run effects, and accounting for firm heterogeneity. Substantively, by focusing on 17 subsectors of Iran's food industry and integrating structural shocks (exchange rate, energy costs, input costs, market concentration) with behavioral shocks (advertising expenditures and innovative value added) into a unified framework, this study asks: what is the relative contribution of each factor to shaping market power under Iran's specific economic conditions? Grounded in the SCP framework and inspired by Mydland *et al.* (2022), this research analyzes the dynamics of market power in Iran's food industry. Yet, through its methodological innovation—employing the PSVAR model and focusing on shock transmission—it moves beyond prior work and offers fresh insights for industrial policy and firm strategy in this critical sector.

Analyzing market power not only clarifies competitive dynamics and their impact on pricing and quality but also supports policies designed to promote fair competition and protect consumer welfare.

The research questions are as follows: How do shocks to market power in Iran's food industry operate within the SCP framework? Do the effects of these shocks vary across subsectors and over time? What are the policy implications of these findings?

The remainder of the paper is structured into four sections. The Materials and Methods section reviews the relevant literature, data sources, and empirical strategy. The third section presents the results and discussion. The fourth section concludes and offers policy recommendations.

Materials and Methods

Economic theory suggests that economies benefit from competition among firms. A lack of competition often results in prices above the marginal cost of production, meaning consumers pay more than the incremental cost of supplying a product. Ideally, society would like to minimize such deadweight losses. Perfect competition—even if rarely attainable in practice—where prices equal marginal costs ($P = MC$), serves as a normative benchmark for well-functioning markets. The problem arises when producers exercise pricing power, resulting in $P > MC$. One might initially suspect that high output prices reflect high production costs, such as elevated wages (Mydland *et al.*, 2022).

Recent evidence, however, indicates that markups have increased over recent decades, both in Europe (Weche & Wambach, 2021) and in the United States (De Loecker, Eeckhout, & Unger, 2020). Markups are a key indicator of market power and deviation from perfect competition. In theory, under competitive conditions, markups should erode and converge toward zero in the long run. In practice, however, real-world markets often exhibit persistent positive markups, signaling the exercise of market power and associated welfare losses. Consequently, identifying the determinants of markups is of paramount importance.

The baseline model of this study draws on Kumbhakar *et al.* (2012) and Mydland *et al.* (2022), but extends their work by incorporating firm heterogeneity and a richer set of determinants—particularly shocks specific to the Iranian economy—thereby offering a more precise, context-sensitive analysis of market power in Iran's food industry.

Efficient production technology is characterized by a standard production function $Y = f(X, T)$, or more generally a transformation function $F(Y, X, T) = 1$, where Y denotes output, X is a vector of inputs, and T is a shifter of the production function, distinct from X. In practice, T is often replaced with a time trend. By duality, all features of the production technology captured by $Y = f(X, T)$ can be uniquely represented by a minimum total cost function $C(W, Y, T)$, where C is minimum total cost and W is the vector of input prices. Hence, all properties of the production function can be derived from the cost function, or conversely, cost function properties can be recovered from the production function. Importantly, these approaches differ in their data requirements: estimating the cost function requires information on input prices, whereas estimating the production function does not.

When product markets are competitive (an assumption maintained in deriving the cost function), the product price equals marginal cost (MC), and the markup component is zero. Consequently, if $P > MC$, a positive markup is said to exist. To compute MC, we first estimate a cost function, then derive MC from it. The firm-level markup is then calculated as $(P - MC)/MC$. A positive markup indicates non-competitive behavior in the product market. This approach follows De Loecker & Warzynski (2012), although De Loecker *et al.* (2020) raised concerns, noting that prices may also be high due to large fixed costs.

Assuming that $P > MC = \partial C / \partial Y$, it follows that:

$$\frac{PY}{C} > \frac{MC \cdot Y}{C} = \left(\frac{\partial C}{\partial Y}\right)\left(\frac{Y}{C}\right) = \frac{\partial \ln C}{\partial \ln Y}, \qquad (1)$$

where PY/C is the share of revenue in total cost. Inequality (1) can be turned into an equality by introducing a non-negative one-sided term u:

$$\frac{PY}{C} = \frac{\partial \ln C}{\partial \ln Y} + u \Longrightarrow RS = E_{cy} + u, u \geq 0, \qquad (2)$$

Where $RS = PY/C$ and E_{cy} is the cost elasticity. In equation (2), u represents the markup. However, u cannot be directly recovered from the data because $\partial \ln C/\partial \ln Y$ must be obtained from an estimated cost function. Moreover, the revenue share may be contaminated by unobserved factors. We assume that such noise is captured by a symmetric two-sided error term ν. Including ν in (2) renders the equation analogous to a stochastic frontier (SF) specification. Thus, we draw on the efficiency literature and employ the SF approach to estimate markups at the observation level.

Estimating a cost function requires adequate variation in input prices. This limitation can be circumvented by using an input distance function (IDF), which depends only on input and output quantities. Starting from the transformation function $F(Y, X, T) = 1$ and exploiting the linear homogeneity (degree one) of the IDF in inputs, we obtain:

$$-\ln X_1 = \ln F(1, X^*, Y, T) \Longrightarrow \ln X_1 = \ln F(X^*, Y, T),$$

where $X_k^* = X_k/X_1$. Because the IDF is dual to the cost function (Färe & Primont, 2012), we have $E_{cy} = (\partial \ln X_1)/\partial \ln Y$. For a translog IDF, this elasticity takes the form:

$$E_{cy} = \beta_y + \sum_{k=2}^{J} \beta_{jk} \ln X_k^* + \gamma_{yy} \ln Y + \beta_{yt} T. \qquad (3)$$

Substituting (3) into (2) yields:

$$RS = E_{cy} + u = \beta_y + \sum_{k=2}^{J} \beta_{jk} \ln X_k^* + \gamma_{yy} \ln Y + \beta_{yt} T + u. \qquad (4)$$

Thanks to duality and the use of the IDF, estimating (4) does not require input price data—a distinct practical advantage.

Given the panel structure of our data, we extend the model in (4) along several dimensions. Crucially, we do not compute u directly from (4), as u might reflect random outcomes unrelated to true markups. To address this, we augment (4) with a noise term incorporating firm-specific unobserved heterogeneity, denoted $\upsilon_{it} + \mu_i$. We further introduce observable determinants of markups by specifying u_{it} as a function of variables Z_{it}. This specification allows us to control for measurement error in the revenue share as well as unobserved firm fixed effects when estimating markups.

Final Estimation Model

The final model to be estimated is thus specified as:

$$RS_{it} = \beta_y + \sum_{k=2}^{J} \beta_{jk} \ln X_{kit}^* + \gamma_{yy} \ln Y_{it} + \beta_{yt} T_{it} + \mu_i + \upsilon_{it} + u(Z_{it}), i = 1, \ldots, N; t = 1, \ldots, T.$$

$$u = RS_{it} + \sum_{k=2}^{J} \vartheta_{jk} \ln Z_{kit}^* - \left(\beta_y + \sum_{k=2}^{J} \beta_{jk} \ln X_{kit}^* + \gamma_{yy} \ln Y_{it} + \beta_{yt} T_{it} + \mu_i + \upsilon_{it}\right) \qquad (5)$$

Determinants of Markups and Market Power

Drawing on the SCP framework, the determinants of markups and market power in the food industry can be categorized into three broad groups:

Structural and Geographical Determinants

Firm size and economies of scale (Kroupova *et al.*, 2025), geographic concentration and cluster benefits (Kroupova *et al.*, 2025), and physical location (Mydland *et al.*, 2022) directly influence a firm's ability to set prices above marginal cost.

Behavioral and Strategic Determinants

Advertising and branding strategies foster product differentiation and consumer loyalty, thereby reducing demand elasticity and increasing markups (Apelbaum, 1999; Ma *et al*., 2021; Irz & Liu, 2016). Similarly, investment in research and development (R&D) enhances product quality and innovation, further strengthening markups (Ma *et al*., 2021).

Policy, market structure, and macroeconomic determinants:

Government Policies

Antitrust enforcement, subsidies, and tax policies can either constrain or expand the scope for exercising market power (Ma *et al*., 2021; Sexton & Xia, 2018).

Market Structure

The degree of industrial concentration, competition patterns, and retailer bargaining power (e.g., through private labels) affect profit margins (Cacchiarelli & Sorrentino, 2019; Kroupova *et al*., 2025).

Macroeconomic Factors

Globalization (Syverson, 2019), innovation, ESG criteria (Lu, 2024), shifting consumer preferences (Tripathy, 2025), and financial frictions (Syverson, 2019) shape markup dynamics by influencing costs, demand, and competitiveness.

Although these factors have been extensively examined in both international and domestic studies, a dynamic, simultaneous, and quantitative analysis of the interactions and relative impacts of shocks from these structural, behavioral, and macroeconomic factors on market power—specifically within the unique context of Iran's food industry and using structural methods such as panel SVAR—remains largely unexplored. This study aims to fill that gap.

Data Description

This study employs panel data covering 17 four-digit ISIC subsectors of Iran's food industry from 2002 to 2022 (1381–1401 Iranian calendar). These subsectors include: meat processing and preservation; fish, crustacean, and mollusk processing and preservation; fruit and vegetable processing and preservation; manufacture of vegetable and animal oils and fats (excluding corn oil); manufacture of dairy products; manufacture of grain mill products; manufacture of starches and starch products; manufacture of sugar; manufacture of cocoa, chocolate, and sugar confectionery; manufacture of macaroni, noodles, vermicelli, and similar farinaceous products; manufacture of prepared meals and dishes; manufacture of bakery and farinaceous products (excluding sweet bakery); manufacture of other food products not elsewhere classified; manufacture of prepared animal feeds; manufacture of soft drinks; production of mineral and other bottled waters; manufacture of malt; and distillation, rectification, and blending of spirits.

The key variables include the exchange rate, energy costs, firm size, value added, advertising expenditures, intermediate input costs, and the Lerner index.

The dataset contains information on output, capital, labor, intermediate inputs, energy costs, the free-market dollar exchange rate, prices, number of establishments, firm sales, and firm-level advertising expenditures, enabling the estimation of the Lerner index and other relevant indicators. The sample period is determined by the most recent available data. All data were obtained from the Industrial Workshop Survey conducted by the Statistical Center of Iran and from the Central Bank of Iran.

All nominal financial variables were deflated to constant prices using the Producer Price Index (PPI) with 2016 (1395) as the base year. The PPI was preferred over general price indices (such as the GDP deflator) because it more directly reflects price changes at the producer level and is better suited to the nature of industrial data.

Estimation Approaches for Markups

The literature offers a wide range of approaches for estimating markups, with no clear consensus on a single "best" method. In the mid-1980s, the Structure-Conduct-Performance (SCP) paradigm was widely used, wherein economic performance was typically proxied by price-cost margins (e.g., Sheldon & Sperling, 2003; Garcia *et al*., 2022). The SCP framework posits a one-way causal chain from market structure to conduct and then to performance. Subsequently, structural modeling and total cost function estimation gained popularity (e.g., Hyde & Perloff, 1995; Wolfram, 1999; Størdal & Baardsen, 2002). More recently, the New Empirical Industrial Organization (NEIO) approach has been extensively applied. NEIO estimates markups without directly estimating marginal costs, typically by recovering the markup from a supply relation that controls for the determinants of marginal cost (Appelbaum, 1982; Bresnahan, 1982). Perekhozhuk et al. (2017) provide a detailed description of two common NEIO methods—the Production Theory Approach (PTA) and the General Identification Method (GIM). Building on Hall's (1988) methodology, De Loecker (2011) and De Loecker & Warzynski (2012) introduced the Production Function Approach (PFA), which recovers markups from estimates of a production function using production data alone. This approach has been widely adopted in recent studies (e.g., De Loecker *et al*., 2020; Weche & Wagner, 2021).

Production Function Specification

In this study, we adopt a structural approach using the production function method. The production function for industry i in year t is specified as:

$$Q_{it} = A_{it} f(l_{it}, k_{it}, M_{it}) \tag{6}$$

where Q_{it} denotes output, l_{it} is labor input, k_{it} is capital stock, A_{it} is total factor productivity, and M_{it} represents intermediate inputs.

The firm's cost minimization problem is:

$$\min_{L,K,M} \; W_{it}L_{it} + r_{it}K_{it} + P_{it}^{m}M_{it}$$

$$\text{subject to } A_{it}F(L_{it}, K_{it}, M_{it}) \geq Q_{it} \tag{7}$$

Here, w, r, and P_m denote the prices of labor, capital, and intermediate inputs, respectively. Solving the Lagrangian yields the first-order condition with respect to the intermediate input:

$$P_{it}^{m} = \lambda_{it} \frac{\partial F_{it}}{\partial M_{it}} \tag{8}$$

where λ_{it} is the marginal cost of production. Multiplying both sides by M_{it}/Q_{it} and rearranging gives:

$$\frac{\partial F_{it}}{\partial M_{it}} \frac{M_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{m} M_{it}}{P_{it} Q_{it}} P_{it} = \frac{P_{it}}{\lambda_{it}} \frac{P_{it}^{m} M_{it}}{P_{it} Q_{it}} \tag{9}$$

Let $\mu_{it} = P_{it}/\lambda_{it}$ denote the markup. Then, following Khodadkashi *et al*. (2018), we obtain:

$$\mu_{it} = \theta_{it}^{m} (\alpha_{it}^{m})^{-1} \tag{10}$$

where $\theta_{it}^{m} = \frac{\partial F_{it}}{\partial M_{it}} \frac{M_{it}}{Q_{it}}$ is the output elasticity with respect to intermediate inputs, and $\alpha_{it}^{m} = \frac{P_{it}^{m} M_{it}}{P_{it} Q_{it}}$ is the revenue share of intermediate inputs.

Because computing θ_{it}^{m} requires estimating the production function, we must select an appropriate functional form. While Cobb-Douglas and CES specifications are common, the translog functional form is preferred due to its flexibility: it nests simpler forms and allows second-order derivatives. However, without imposing regularity conditions, the translog may not satisfy monotonicity and concavity unless the data are sufficiently rich.

We specify a translog production function with two fixed inputs (labor L_{it} and capital K_{it}), which face high adjustment costs, and one variable input (intermediate inputs M_{it}). The logarithmic form is:

$$\begin{aligned}\ln Q_{it} = {} & \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \beta_3 \ln M_{it} \\ & + \beta_{11}(\ln L_{it})^2 + \beta_{22}(\ln K_{it})^2 + \beta_{33}(\ln M_{it})^2 \\ & + \beta_{12} \ln L_{it} \ln K_{it} + \beta_{13} \ln L_{it} \ln M_{it} + \beta_{23} \ln K_{it} \ln M_{it} \\ & + \beta_{123} \ln L_{it} \ln K_{it} \ln M_{it}\end{aligned} \tag{11}$$

where T is a time trend. The output elasticity with respect to intermediate inputs is then:

$$\begin{aligned}\theta_{it}^{m} = \frac{\partial \ln Q_{it}}{\partial \ln M_{it}} = {} & \hat{\beta}_3 + 2\hat{\beta}_{33} \ln M_{it} + \hat{\beta}_{13} \ln L_{it} \\ & + \hat{\beta}_{23} \ln K_{it} + \hat{\beta}_{123} \ln L_{it} \ln K_{it} \\ & + \hat{\beta}_{34} T\end{aligned} \tag{12}$$

After estimating the coefficients of the translog production function from equation (11), we compute the markup and the Lerner index as:

$$\mu_{it} = \hat{\theta}_{it}^{m}(\alpha_{it}^{m})^{-1},$$

$$\text{Lerner}_{it} = \frac{\mu_{it}}{\mu_{it}+1} \quad (13)$$

Market Concentration: Herfindahl-Hirschman Index (HHI)

To measure market concentration, we use the Herfindahl-Hirschman Index (HHI), defined as:

$$HHI_{it} = \sum_{i=1}^{n} s_{it}^{2} \text{ ,where } s_{it} = \frac{x_{it}}{x}, \sum_{i=1}^{n} s_{it} = 1, 0 < s_{it} < 1 \quad (14)$$

Here, n is the number of firms, x_{it} is the output of firm i, and x is total industry output. When market shares are expressed as percentages, the HHI ranges from 0 to 10,000. A value of 0 indicates perfect competition; 10,000 indicates pure monopoly. Following standard guidelines (Akhani *et al.*, 2024), an HHI below 1,000 indicates an unconcentrated market; between 1,000 and 1,800 indicates moderate concentration; and above 1,800 indicates high concentration.

Capital Stock Estimation

Estimating the production function requires capital stock data. Due to the lack of official disaggregated capital stock statistics at the four-digit industry level, we estimate capital stock using the exponential method. This method uses investment data from 2002 to 2022 for the 17 four-digit food industry subsectors.

We begin with the exponential investment function and Taking logarithms:

$$I_i = I_{it}e^{it}$$

$$\ln I_i = \ln I_0 + \lambda T + u_i \quad (15)$$

Taking the antilogarithm of the intercept and dividing by the investment growth rate (the coefficient of the time variable) yields the base-year capital stock (K_0) without depreciation:

$$K_0 = \frac{I_0}{\lambda} \quad (16)$$

After obtaining the base-year capital stock, we use the Klein method to compute capital stock in subsequent periods:

$$K_{it} = K_0 + \sum_{i=1}^{t}(I-D)_i \quad (17)$$

In equation (17), the depreciation rate (D) is set at 0.04 (4%) for all industries. This rate is consistent with international standards and is reasonable for the food industry. The same rate has been used in reputable domestic studies (e.g., Akhani *et al.*, 2024), implying an average useful life of approximately 25 years for processing machinery and equipment, which is conventional for this sector.

The Structural Vector Autoregression (SVAR) model has become a widely used econometric tool among empirical researchers, particularly those interested in studying the dynamics among economic variables. the SVAR framework was developed by imposing theoretical restrictions on the contemporaneous effects of shocks. Subsequently, Blanchard and Quah (1989), Gali and Clarida (1994), and Ahmed and Gerrat (1996) identified impulse response functions by imposing theoretical restrictions on the long-run effects of shocks.

Unlike unrestricted VAR models, where the identification of structural shocks is often implicit and ad hoc, the SVAR approach explicitly incorporates an economic rationale or economic theory to impose identifying restrictions. However, as is common in many econometric frameworks, countless studies could be conducted using the SVAR approach, but the lack of time series data with sufficient length often prevents this. This problem can be partially addressed using the novel Panel SVAR (PSVAR) method. By exploiting cross-sectional variation in panel data, the PSVAR approach compensates to some extent for the lack of long time series. This extended approach is consistent with the traditional time series SVAR literature.

Following Pedroni (2013), the system of equations in the PSVAR approach can be expressed as follows:

$$Y_{i,t} = \Gamma(L)Y_{i,t-1} + \eta_i + \varepsilon_{i,t} \quad (18)$$

Based on equation (18), the panel data generating process (DGP) consists of N cross-sectional units observed over T time periods, each containing a vector of K observable endogenous variables.

The vector of endogenous variables is:

$$Y_{i,t} = (EXCH_{i,t}, ENERGY_{i,t}, SIZE_{i,t}, VA_{i,t}, ADV_{i,t}, M_{i,t}, L_{i,t})$$

where:

- $EXCH_{i,t}$: exchange rate
- $ENERGY_{i,t}$: energy costs
- $SIZE_{i,t}$: firm size (concentration index)
- $VA_{i,t}$: value added
- $ADV_{i,t}$: advertising expenditures
- $M_{i,t}$: intermediate input costs
- $L_{i,t}$: markup / market power (Lerner index)

The main objective of this study is to investigate the shocks affecting Iran's food industry on markups or market power.

The model parameters are presented in matrix A, which captures the contemporaneous correlations among the model variables and embodies the identification assumptions. To eliminate fixed effects and simplify notation, the transformed data vector is defined as:

$$\tilde{Y}_{i,t} = Y_{i,t} - \bar{Y}_i \qquad (19)$$

where $\bar{Y}_i$ is the cross-sectional mean. In the PSVAR model, the vector of structural shocks, $\varepsilon_{i,t}$, is assumed to be white noise (Pedroni, 2013).

Identification Strategy: Blanchard-Quah Approach

Following Blanchard and Quah (1989), the identification of structural shocks is achieved by imposing a series of restrictions on the long-run effects of shocks on certain variables. The number of effective restrictions on the PSVAR equation equals $K(K-1)/2$ imposed on the $A(1)$ matrix. In the present study, given the number of variables ($K = 7$), the number of restrictions is 21. The ordering of variables in the $A(1)$ matrix proceeds from least endogenous to most endogenous.

The structural disturbance vector is $\varepsilon = (\varepsilon^{exch}, \varepsilon^{energh}, \varepsilon^{HHI}, \varepsilon^{VA}, \varepsilon^{adv}, \varepsilon^{M}, \varepsilon^{L})'$,

where:

ε^{L}: market power shock

- ε^{M}: intermediate input cost structure shock
- ε^{adv}: advertising cost shock
- ε^{VA}: value added shock
- ε^{HHI}: firm size (concentration index) shock
- ε^{energh}: energy and fuel shock
- ε^{exch}: exchange rate shock

Following the Blanchard-Quah approach, three sets of restrictions are imposed to achieve identification in the markup model:

$$\begin{bmatrix} \varepsilon^{exch} \\ \varepsilon^{energh} \\ \varepsilon^{HHI} \\ \varepsilon^{VA} \\ \varepsilon^{adv} \\ \varepsilon^{M} \\ \varepsilon^{L} \end{bmatrix} = \begin{bmatrix} + & 0 & 0 & 0 & 0 & 0 & 0 \\ + & + & 0 & 0 & 0 & 0 & 0 \\ + & + & + & 0 & 0 & 0 & 0 \\ - & - & + & + & 0 & 0 & 0 \\ + & + & + & + & + & 0 & 0 \\ + & + & - & - & - & + & 0 \\ - & - & + & + & + & - & + \end{bmatrix} \begin{bmatrix} u^{exch} \\ u^{energh} \\ u^{HHI} \\ u^{VA} \\ u^{adv} \\ u^{M} \\ u^{L} \end{bmatrix} \qquad (20)$$

First Set of Restrictions: Small Open Economy Assumption

The first set of restrictions relates to the small open economy assumption. These restrictions implicitly state that domestic shocks have no long-run effects on external variables. In other words, market power, intermediate costs, advertising, value added, firm size, and energy cost shocks have no long-run effect on the exchange rate. These restrictions imply zero values in the northeast quadrant of the coefficient matrix. Thus, in the first row, all elements except a_{11} are zero.

Second Set of Restrictions: Theoretical Long-Run Effects

The second set of restrictions, derived from the theoretical model, imposes constraints on the long-run effects of structural shocks on domestic endogenous variables. These restrictions correspond to zeros in the southeast quadrant of the $A(1)$ matrix, meaning that a particular structural disturbance does not have a long-run effect on the level of certain endogenous variables.

The exchange rate, energy costs, and intermediate input costs—as key factors affecting production costs and market structure—are consistent with the theoretical foundations of market power and the Lerner index. The exchange rate, especially in food industries with international markets, can influence firms' pricing power through its effect on imported raw material costs and export competitiveness. According to the theoretical framework of globalization, exposure to international trade acts as a disciplinary force on profit margins (Syverson, 2019), which can either decrease or increase the Lerner index, depending on whether firms gain more market power in export markets or face intensified competition. Energy costs and intermediate input costs, as major components of production costs, directly affect firms' marginal costs and alter the Lerner index through their effect on the price-to-marginal cost ratio. In the food industry, reducing production costs through industrial clusters or economies of scale (as noted in Kroupova *et al*., 2025) can increase profit margins and raise the Lerner index, especially in regions with strong infrastructure (Mydland *et al*., 2022).

Firm size (concentration index) and advertising expenditures, as structural and behavioral factors within the SCP framework, are well-aligned with the theoretical foundations of market power. Firm size, often measured by market concentration indices such as the Herfindahl-Hirschman Index (HHI), has a positive effect on the Lerner index because larger firms benefit from economies of scale, better access to capital, and greater bargaining power (Kroupova *et al*., 2025). This is evident in the food industry, particularly in sectors such as grains and meat, where market power increases retail margins by up to 60% (Irz & Liu, 2016). Advertising expenditures, by creating product differentiation and brand loyalty, generate inelastic demand, thereby raising the Lerner index through increased pricing power (Ma *et al*., 2021). Empirical evidence suggests that advertising intensity serves as a proxy for market power and has a strong correlation with the Lerner index (Wang *et al*., 2025). These variables increase markups by enhancing strategic positioning and reducing perceived substitutes, especially in food retailing (Apelbaum, 1999).

Value added, as a measure of productivity and innovation, is consistent with theoretical foundations related to innovation and resource allocation and has a direct impact on the Lerner index. Innovation, through research and development (R&D), increases profit margins by enhancing product quality and creating differentiation, leading to a higher Lerner index (Syverson, 2019). In the food industry, value added is created through improvements such as quality, packaging, and sustainability, which strengthen consumer demand and increase market power (Lu, 2024; Ma *et al*., 2021). Furthermore, value added can indicate efficiency in resource use, which raises the Lerner index by reducing marginal costs.

Third Set of Restrictions: Orthogonality of Structural Shocks

The third set of restrictions, necessary to complete the identification process, assumes no correlation among structural shocks. In practice, this assumption is implemented through the Cholesky decomposition of the variance-covariance matrix of model residuals, considering a specific ordering of variables (equation 20) based on their relative endogeneity. This ordering produces orthogonal shocks and ultimately enables full identification of the $A(1)$ matrix and the computation of impulse response functions.

It should be noted that to analyze the effects of shocks—namely, impulse response functions and variance decomposition—we used EViews software, following Pedroni (2013).

Results and Discussion

Before estimating the Lerner index, unit root tests were conducted for all variables. Table 1 presents the PP-Fisher unit root test results for the production function variables. As shown, all variables are stationary at the 5% level. The F-test confirmed the panel structure of the model. The Hausman test indicated that the random effects model is appropriate. The White test revealed heteroscedasticity ($p< 0.05$), so GLS estimation was employed. The Jarque-Bera normality test (statistic= 1.86) indicated that the error terms are normally distributed.

Table 1- Unit root test of variables under study in the model at the level

Variables under investigation	PP-Fisher	
	Statistics	**Probability**
Logarithm of production	301.102	0.004
Logarithm of employment	303.062	0.003
Logarithm of employment × Logarithm of employment	319.444	0.000
Logarithm of capital stock	2586.38	0.000
Logarithm of capital stock × Logarithm of capital stock	2489.54	0.000
Logarithm of intermediate input cost	303.43	0.003
Logarithm of intermediate input cost × Logarithm of intermediate input cost	300.25	0.005
Logarithm of employment × Logarithm of capital stock	313.75	0.000
Logarithm of intermediate input cost × Logarithm of capital stock	284.41	0.052
Logarithm of intermediate input cost × Logarithm of employment	305.75	.0002
Logarithm of intermediate input cost × Logarithm of employment × Logarithm of capital stock	306.86	.0001
Logarithm of capital stock × Time	556.49	0.000
Logarithm of employment × Time	308.47	0.001
Logarithm of intermediate input cost × Time	244.41	0.057

Source: Researcher's findings

Table 2 presents the panel data estimation results for the translog production function. The overall model is significant (F-statistic probability< 0.05). The R^2 and adjusted R^2 values (0.95) indicate that 95% of the variation in the dependent variable is explained by the independent variables. Some interaction terms ($lnL{\cdot}lnK{\cdot}lnM$, $lnK{\cdot}T$, $lnM{\cdot}T$) are not statistically significant. Based on these estimation results, markups and Lerner indices were calculated for each of the 17 four-digit subsectors over the period 2002–2022.

Before estimating the PSVAR models, the stationarity of all study variables was examined. For this purpose, the Levin, Lin & Chu (LLC) test was used to test for panel unit roots. Table 3 presents the LLC unit root test results. As observed, the null hypothesis of non-stationarity is rejected for all variables, confirming that all model variables are stationary. Having established stationarity, there is no need for cointegration tests.

Table 4 presents the optimal lag length selection criteria. Although alternative criteria (AIC, HQ, FPE) suggested an optimal lag of 8, the Schwarz criterion (SC) selected lag 1. Given that choosing a larger lag would result in a greater loss of degrees of freedom, lag 1 was selected as the optimal lag based on the Schwarz test. Stability tests confirmed that all eigenvalues lie within the unit circle, indicating model stability (Appendix 1).

Among the shocks examined (excluding the variable's own shock), intermediate input cost structure and value added shocks have the largest effects on markups in the first period. Energy cost and advertising cost shocks follow in terms of impact magnitude.

Table 2- Results of the panel data model for estimating the Lerner index

Variables under investigation	Result estimation	
	Statistics	**Probability**
Intercept	0.748	0.432
Logarithm of employment	1.402	0.000
Logarithm of capital stock	-0.324	0.003
Logarithm of intermediate input cost	0.201	0.038
Logarithm of employment × Logarithm of employment	0.094	0.000
Logarithm of capital stock × Logarithm of capital stock	0.009	0.000
Logarithm of intermediate input cost × Logarithm of intermediate input cost	0.038	0.000
Logarithm of employment × Logarithm of capital stock	-.0073	0.000
Logarithm of intermediate input cost × Logarithm of capital stock	0.071	0.000
Logarithm of intermediate input cost × Logarithm of employment	-0.162	0.000
Logarithm of intermediate input cost × Logarithm of employment × Logarithm of capital stock	0.0001	0.844
Time	0.068	0.000
Time × Time	0.001	0.001
Logarithm of capital stock × Time	-0.001	0.261
Logarithm of employment × Time	0.006	0.013
Logarithm of intermediate input cost × Time	-0.001	0.296
R-squared	0.95	
Adjusted R-squared	0.95	
F	0.000	**3257/57**

Source: Researcher's findings

Table 3- Unit root test of variables under study in the model at the level

Variables under investigation	LLC	
	Statistics	Probability
EXCH	-5.35353	0.0000
ENERGH	-3.93858	0.0000
HHI	-5.327	0.0548
ADV	- 9.3001	0.0000
M	-7.74475	0.0000
VA	- 5.1771	0.0952
L	-1.68923	0.0456

Source: Researcher's finding

Table 4- Optimal LAG determination test

LAG	HQ	SC	AIC	LR	LogL
0	14.81	14.87	14.76	NA	-1617.44
1	1.87	* 2.39	1.52	2900.93	-112.24
2	1.96	2.92	1.30	137.05	-38.70
3	2.30	3.72	1.34	80.14	5.82
4	2.34	4.21	1.08	135.56	83.89
5	1.75	4.06	0.18	247.75	232.00
6	1.74	4.51	-0.12	133.94	315.25
7	1.58	4.80	-0.59	154.70	415.35
8	1.62*	5.29	* -0.86	* 116.331	493.86

Source: Researcher's finding

Exchange rate shock induces an immediate negative response in the Lerner index during the first two to three periods. This occurs because increased imported raw material costs reduce profit margins and force firms to lower prices to maintain market share, consistent with the competitive pressures of international trade (Syverson, 2019). The return of this effect to zero indicates firms' gradual adjustment to new exchange rate conditions.

Energy cost shock also generates a negative response, as rising production costs—particularly in Iran's food industry, which is affected by energy subsidies—reduce profit margins and weaken the pricing power of smaller firms (Akhani *et al*., 2024).

Market concentration shock (HHI) produces a positive and diverging response in the Lerner index. Reduced structural competition and enhanced economies of scale in concentrated markets, such as the bread and beverage sectors, increase firms' pricing power (Kroupova *et al.*, 2025; Irz & Liu, 2016; Khodadkashi *et al.*, 2018). The temporal divergence emphasizes the importance of considering the time horizon and institutional dynamics in market structure analysis.

Value added shock generates a positive response. Innovation and product quality improvements through sustainability (ESG) and packaging reinforce inelastic demand and increase profit margins, consistent with the role of productivity in market power (Syverson, 2019; Lu, 2024; Ma *et al*., 2021).

Advertising cost shock has a mild effect on the Lerner index. The widespread use of advertising in food retail neutralizes product differentiation effects and leads to competitive equilibrium (Ma *et al*., 2021; Apelbaum, 1999). In other words, advertising in Iran's food industry is primarily informational and, due to legal constraints, media concentration, and consumer price sensitivity, plays a limited role in product differentiation and increasing market power. This finding is consistent with Iran's market structure, which is more influenced by exchange rates, energy subsidies, and input costs. Thus, advertising in this industry is a supplementary cost with no significant impact on competitiveness.

Intermediate input cost shock has a negative and significant effect on market power, consistent with theory. According to pricing theory, an increase in average cost reduces profit margins, which lowers the Lerner index.

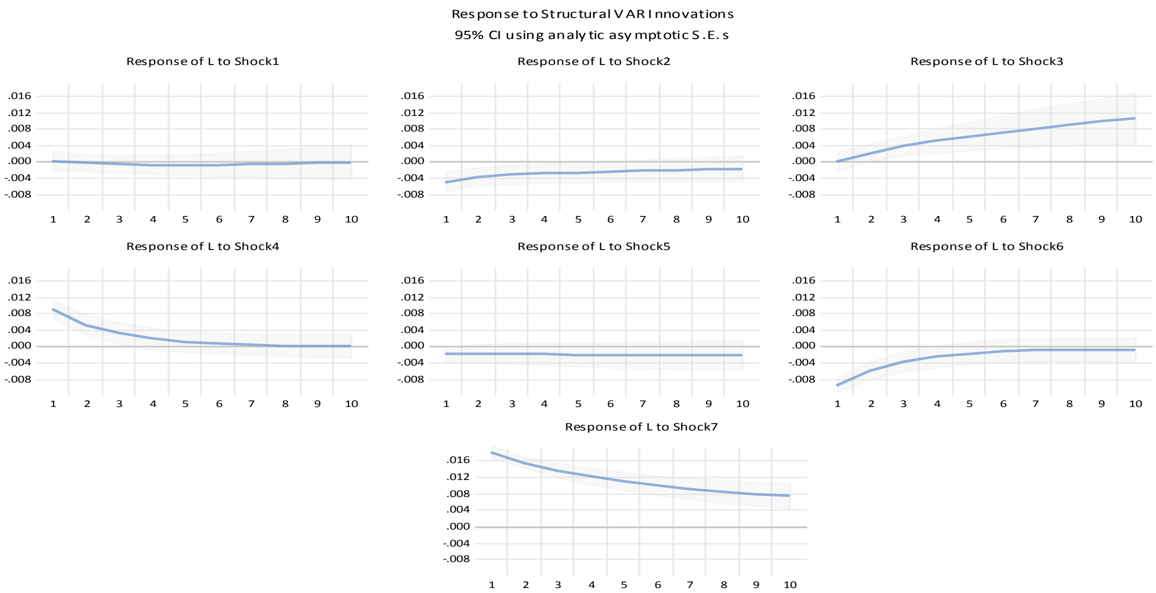


Chart 1- The effect of Impulse Response Function (IRF) on the market power of industries in Iran
Source: Researcher's findings

These findings, by combining structural factors (concentration, value added), behavioral factors (advertising), and production costs (exchange rate, energy, intermediate inputs), provide a comprehensive understanding of market power dynamics in Iran's food industry, highlighting the key role of market structure and innovation in strengthening profit margins. From an economic perspective, price determination and market power formation in Iran's food industry are more dependent on variables such as the exchange rate, energy subsidies, market regulation policies, and input costs than on advertising and branding. In such a structure, advertising plays a minor role in changing consumer behavior or redistributing market share.

From a behavioral perspective, domestic consumers in the food sector are more sensitive to price than to brands or advertising. In other words, consumer decision-making in this area is more based on price and product availability than on the extent of brand advertising. Consequently, even increases in firms' advertising expenditures do not lead to significant changes in market power (Lerner index).

Variance Decomposition

Variance decomposition indicates the relative contribution of each variable to the variation in other variables. Table 5 presents the variance decomposition of common shocks on market power.

Table 5- Analysis of variance Decomposation of market power of industries in Iran

Period	S.E.	Market power shock	Value added shock	Intermediate cost shock	Advertising shock	Market size shock	Energy cost shock	Exchange rate shock
1	0.23	62.15	17.0	0.68	15.61	0.002	4.49	0.01
2	0.33	66.59	14.68	0.74	12.95	0.55	4.44	0.01
3	0.42	69.07	12.80	0.85	11.04	1.75	4.41	0.04
4	0.50	70.03	11.33	1.00	9.64	3.53	4.36	0.07
5	0.57	69.87	10.16	1.16	8.58	5.79	4.30	0.10
6	0.65	68.91	9.21	1.33	7.73	8.45	4.22	0.12
7	0.72	67.37	8.42	1.47	7.04	11.42	4.11	0.12
8	0.80	65.43	7.75	1.60	6.45	14.64	3.98	0.12
9	0.87	63.20	7.16	1.68	5.93	18.04	3.83	0.12
10	0.95	60.77	6.64	1.73	5.47	21.57	3.67	0.11

Source: Researcher's findings

The results show that among the shock variables, the largest share (17%) in explaining variation in market power is attributable to intermediate input costs. The relative share of exchange rate shocks in market power variation is 0.01% in the first period, gradually increasing over time. The share of energy and fuel cost shocks is 4.49%. The smallest share is for concentration (firm size) shocks, although its contribution increases over the 10-year horizon. The share of value added and output shocks on market power is over 15%, with a gradual decline over time. Advertising cost shocks have a 0.68% share in market power variation.

The variance decomposition analysis of market power (Lerner index) in the food industry reveals that firm costs are the most important factor affecting market power variation, with a substantial portion of this indicator's fluctuations depending on this factor. Output and value added also play significant roles. The exchange rate has a limited effect initially, but its importance increases over time, likely due to the food industry's dependence on imports or exports. Concentration/firm size has the smallest impact, although its role gradually becomes more prominent, potentially reflecting firm growth or structural changes in the industry. Advertising costs have a negligible role, indicating the limited impact of advertising strategies on market power in this industry. Overall, to strengthen market power in the food industry, focusing on firm cost management and production optimization may be more effective than other factors, while attention to long-run exchange rate trends and firm structure is also essential.

Conclusion

In general, analyzing market power in the food industry is of great importance. This issue not only affects competition and pricing but can also influence food safety and economic welfare. By analyzing the factors affecting market power, stakeholders can better navigate the complexities of the food market and implement policies to promote fair competition and protect consumer interests.

This study aimed to investigate the effects of shocks on market power in 17 Iranian industrial firms following Mydland *et al.* (2022) within the Structure-Conduct-Performance (SCP) framework at the four-digit ISIC level over the period 2002–2022 using a Panel SVAR model. Accordingly, a translog production function was used to calculate market power in Iran's food industries. Capital stock was calculated using the Klein method. Exchange rate, fuel and energy costs, concentration index, value added, advertising costs, and intermediate input costs were used to examine these effects. The innovations of this study include analyzing the dynamic relationship and econometric model, as well as examining the variables affecting market power within the SCP framework in Iran's food industry.

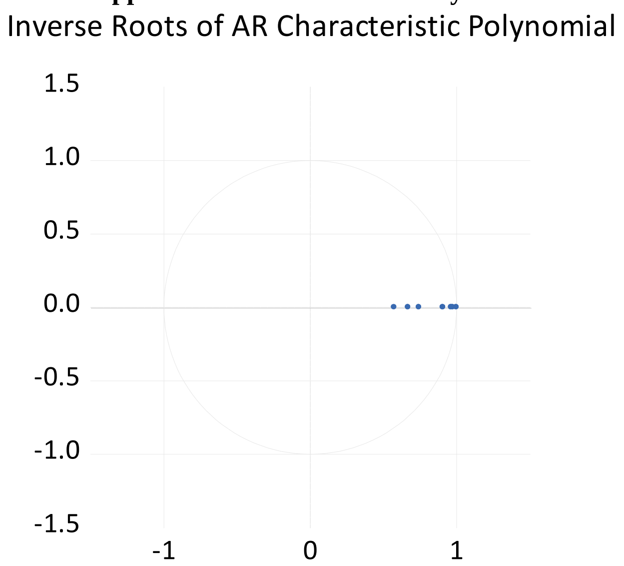
The impulse response and variance decomposition analyses of the Lerner index in Iran's food industry show that market power in this industry is primarily influenced by structural and cost factors such as firm costs, value added, and energy costs, while behavioral factors such as advertising play a limited role. Firm costs, with a substantial share (17%), are the most important determinant of market power variation, indicating the strong influence of production costs on profit margins and firm pricing. Value added and output also play key roles in increasing market power by strengthening demand through innovation and quality improvement, although their effects diminish in the long run. The exchange rate, despite having a small negative initial effect, becomes more important over time due to the industry's dependence on international trade. Energy costs, due to the influence of subsidies and the food industry's sensitivity to production costs, weaken the pricing power of smaller firms.

In contrast, market concentration (HHI) has a positive and diverging effect on the Lerner index by enhancing economies of scale. Reduced structural competition and enhanced scale economies in concentrated markets, such as the bread and beverage sectors, increase firms' pricing power. The temporal divergence emphasizes the importance of considering the time horizon and institutional dynamics in market structure analysis. Advertising, due to legal constraints, media concentration, and domestic consumers' high price sensitivity, has a negligible effect on market power and acts largely as a supplementary cost.

These findings are consistent with the SCP theoretical framework and demonstrate that market power in Iran's food industry is more dependent on structural variables (costs and concentration) and macroeconomic policies (exchange rate and energy subsidies) than on behavioral strategies such as advertising.

From an economic perspective, the dynamics of market power in Iran's food industry reflect the industry's high dependence on cost and structural factors. Firm and intermediate input costs, due to their direct impact on profit margins, play a key role in determining the Lerner index. This implies that firms in this industry must focus on optimizing production costs and managing inputs to maintain competitiveness. The negative effect of the exchange rate in the early periods, particularly due to dependence on imported raw materials, indicates the food industry's vulnerability to exchange rate fluctuations, but the gradual adjustment of firms to new exchange rate conditions demonstrates the industry's relative flexibility. The negative impact of energy costs, given Iran's energy subsidy structure, creates particular challenges for smaller firms that have less capacity to absorb cost shocks. On the other hand, market concentration and economies of scale contribute to increased pricing power, highlighting the importance of market structure in determining competitive power. The limited role of advertising is consistent with domestic consumer behavior, which is primarily sensitive to price and product availability. This suggests that in Iran's food market, branding and advertising strategies alone cannot create sustainable competitive advantage.

Appendix 1- Parameter Stability Tests



Policy Recommendations

1. **Production Cost Management:** Given the key role of firm costs in market power variation, food industry firms should focus on optimizing production processes, reducing waste, and improving input supply chains. The use of modern technologies and efficient production methods can reduce marginal costs and strengthen profit margins.
2. **Strengthening Innovation and Value Added:** Given the positive effect of value added on market power, firms should prioritize investment in innovation, product quality improvement, and sustainability (such as green packaging or ESG criteria). These actions can reinforce inelastic demand and increase pricing power.
3. **Exchange Rate Risk Management:** Given the increasing effect of exchange rates on market power, firms should adopt strategies such as diversifying input supply sources, using exchange rate hedging contracts, or increasing domestic production of raw materials to reduce import dependence.
4. **Focus on Market Structure:** Policies that moderate competition in concentrated markets (such as bread and beverages) can prevent excessive monopoly and balance pricing power. At the same time, supporting economies of scale for larger firms can increase industry productivity.
5. **Revising Advertising Strategies:** Given the limited effect of advertising, firms should focus on targeted information dissemination, digital marketing, and strengthening access to local markets rather than extensive investment in traditional advertising. This approach can reduce unnecessary costs and align with Iranian consumer behavior.
6. **Strengthening Market Regulation Policies:** Policymakers should mitigate the negative effects of external shocks on

market power by establishing appropriate regulations, such as controlling exchange rate fluctuations and supporting domestic production. Creating stability in macroeconomic policies can assist firms in long-term planning.

These recommendations—focusing on cost management, innovation strengthening, and market structure improvement—can enhance the competitiveness and sustainability of Iran's food industry while remaining aligned with the economic and behavioral realities of the domestic market.

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مقاله پژوهشی
جلد ۴۰، شماره ۲، تابستان ۱٤۰۵، ص. ۲۰۹-۱۹۱

اثر تکانه‌های ساختاری و رفتاری بر قدرت بازاری صنایع غذایی در ایران

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تاریخ دریافت:۱۴۰۴/۰۸/۱۳
تاریخ پذیرش:۱۴۰۵/۰۲/۰۷

چکیده

این پژوهش با هدف بررسی اثر تکانه‌های ساختاری و رفتاری بر قدرت بازار در ۱۷ زیربخش (کد چهار رقمی ISIC) صنعت غذایی ایران طی سال‌های ۱۳۸۱ تا ۱۴۰۱ انجام شده است. مطالعه حاضر با به‌کارگیری مدل خودرگرسیون برداری ساختاری تابلویی (PSVAR) در چارچوب ساختار-رفتار-عملکرد (SCP) برای اولین بار در این زمینه، امکان تحلیل پویای تعاملات بین شوک‌های ساختاری و رفتاری را فراهم می‌سازد. متغیرهای ساختاری و رفتاری مورد بررسی شامل نرخ ارز، هزینه انرژی، شاخص تمرکز، ارزش افزوده، هزینه تبلیغات و هزینه نهاده‌های واسطه‌ای بودند. نتایج تجزیه واریانس نشان می‌دهد که بیش از ۸۰ درصد تغییرات قدرت بازار (شاخص لرنر) توسط عوامل ساختاری و هزینه‌ای (شامل هزینه نهاده‌های واسطه‌ای، ارزش افزوده، انرژی و نرخ ارز) توضیح داده می‌شود. هزینه نهاده‌های واسطه‌ای مهم‌ترین عامل اثرگذار منفی بر قدرت بازار شناسایی شده است. تمرکز بازار اثر مثبت و ارزش افزوده نیز از طریق نوآوری، اثر تقویت‌کننده داشته است. در مقابل، عوامل رفتاری مانند تبلیغات، با سهمی کمتر از ۱٪، نقش کاملاً حاشیه‌ای داشته و به‌دلیل محدودیت‌های نهادی و حساسیت قیمتی مصرف‌کننده، نتوانسته‌اند تأثیر معناداری بر قدرت قیمت‌گذاری بنگاه‌ها بگذارند. این یافته‌ها مؤید آن است که قدرت بازار در صنایع غذایی ایران عمدتاً تابعی از ساختار هزینه‌ها، تمرکز صنعتی و سیاست‌های کلان اقتصادی است، نه استراتژی‌های رفتاری بنگاه‌ها. بر این اساس، با توجه به نقش کلیدی عوامل ساختاری و هزینه‌ای در قدرت بازار صنایع غذایی ایران، پیشنهادات سیاستی شامل مدیریت هزینه‌های تولید، تقویت نوآوری و ارزش افزوده، مدیریت ریسک ارزی، تنظیم ساختار بازار، بازنگری در استراتژی‌های تبلیغاتی و تقویت سیاست‌های تنظیم بازار ارائه شده است.

واژه‌های کلیدی: پانل SVAR، شاخص لرنر، صنایع غذایی، قدرت بازاری،
طبقه‌بندی JEL: D24, L11, L60, C33, O14

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https://doi.org/10.22067/jead.2026.96326.1399

Journal of Agricultural Economics & Development

Homepage: https://jead.um.ac.ir

Research Article
Vol. 40, No. 2, Summer 2026, p. 211-236

Determinants of Paddy Market Participation and Intensity in Iran: Evidence from a Generalized Two-Part Fractional Regression Model

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Received: 04 December 2025 Revised: 13 May 2026 Accepted: 16 May 2026 Available Online: 16 May 2026	**How to cite this article:** Habibinodeh, F., Firoozzare, A., Ghorbani, M., & Boccia, F. (2026). Determinants of Paddy market participation and intensity in Iran: Evidence from a generalized two-part fractional regression model. *Journal of Agricultural Economics & Development, 40*(2), 211-236. https://doi.org/10.22067/jead.2026.96839.1407

Abstract

Rice, as the second most important crop after wheat, plays a central role in sustaining rural livelihoods and generating income for farmers in Iran. Despite its importance, structural, institutional, and market-related constraints continue to limit effective commercialization among paddy producers. This study aimed to identify the determinants of both the participation decision and participation intensity in the paddy market of Golestan province. Data were collected during the 2023–2024 cropping season from 150 paddy farmers using a structured and validated questionnaire. The analysis employed a generalized two-part fractional regression model (GTP-FRM), which jointly estimates the binary participation decision and the value-based share of paddy marketed while accounting for the bounded nature of the dependent variable and potential interdependence between stages. The explanatory variables included human capital characteristics (education and household size), asset endowment (cultivated area and mechanization) and institutional and market access variables (milling services, storage facilities, market information, and marketing channels). The results show that 64% of farmers participate in the paddy market, and on average 49% of the gross value of production is sold. Education is negatively associated with paddy market participation, reflecting a strategic shift toward value addition, as more educated farmers tend to process paddy into rice rather than sell raw paddy. In contrast, larger farm size and greater surplus significantly increase participation probability and participation intensity. Institutional and market factors also play differentiated roles: access to market information enhances participation probability, while access to milling facilities encourages rice marketing instead of paddy sales. Overall, the findings suggest that commercialization in Golestan province is shaped not only by production capacity but also by value-addition strategies and transaction-cost considerations within existing policy and market structures. Policies aimed at improving rural processing infrastructure, strengthening market information systems, enhancing surplus generation, and reducing institutional barriers can more effectively support market-oriented behavior and sustainable commercialization among paddy producers in Golestan province.

Keywords: Fractional model, Institutional constraints, Market participation, Rice, Transaction costs

https://doi.org/10.22067/jead.2026.96839.1407

Introduction

Rice, the second most strategic crop after wheat, plays a vital role in Iran's diet and rural economy (Rezaei *et al.*, 2022; Shafieyan & Fadaei, 2017). Given that per capita rice consumption in Iran is about 3.6 times higher than in EU countries, averaging 34.55 kg annually (FAO, 2024), a large share of agricultural activities is devoted to paddy cultivation (Mardani *et al.*, 2022). In Iran, in 2024, approximately 792,543 hectares were under paddy cultivation, producing about 3.4 million tons of paddy, equivalent to roughly 2.04 million tons of milled rice. In this context, Golestan Province stands out as one of the main paddy-producing regions, accounting for nearly 8% of national output (Jehad-Keshavarzi, 2024). Paddy farming has become the principal livelihood for smallholders in the province, ensuring both income generation and household food security (Kazemi & Samouei, 2024). According to the Ministry of Agriculture, around 20.3% of small rural farmers in Golestan cultivate paddy (Jehad-Keshavarzi, 2024). Consequently, improving market participation and access for these farmers is essential for enhancing income, reducing poverty, and promoting rural welfare (Abdullah *et al.*, 2019; Claude *et al.*, 2025; Lopera *et al.*, 2023).

Market participation reflects the extent of farmers' engagement in market activities as sellers (Abate *et al.*, 2022). For paddy producers, this can occur either through selling unprocessed paddy at the farm gate or marketing processed rice with higher value (Denis Ruhinduka *et al.*, 2020). In Iran, smallholder farmers mainly cultivate paddy for household consumption and sell only the surplus, while medium- and large-scale farmers operate more commercially and participate in both paddy and rice markets, where profit margins are greater (Mosavi & Alipour, 2019). Despite this potential, research indicates that paddy producers, particularly smallholders, face persistent challenges across production and marketing stages. These include limited access to inputs, inadequate market infrastructure, and high transaction costs, which together constrain the intensity of their market participation (Ataei *et al.*, 2021; Rezaei *et al.*, 2022). Such difficulties arise from the vulnerability of smallholder supply chains to sudden disruptions, reducing both production efficiency and market performance (Changalima & Ismail, 2022; Orr *et al.*, 2018).

Market participation reflects the extent to which farmers engage in market activities as sellers (Abate *et al.*, 2022). For paddy producers, commercialization may take the form of selling unprocessed paddy at the farm gate or marketing higher-value processed rice, depending on access to post-harvest services and marketing opportunities (Denis Ruhinduka *et al.*, 2020). In Iran, (Mosavi & Alipour, 2019) report that smallholders typically cultivate paddy primarily for household consumption and market only surplus, whereas medium- and large-scale farmers tend to operate more commercially and participate in both paddy and rice markets where margins are higher.

Despite this potential, empirical evidence suggests that paddy producers, particularly smallholders, face persistent constraints across both production and marketing stages, including limited access to inputs, inadequate infrastructure, and high transaction costs (Ataei *et al.*, 2021; Rezaei *et al.*, 2022). These constraints often persist because market services and institutional support are unevenly distributed across locations and farm categories, which amplifies disadvantages for smallholders who have weaker bargaining power and fewer options for value addition. Moreover, smallholder supply chains can be highly vulnerable to disruptions such as climatic shocks, input price fluctuations, and temporary marketing bottlenecks, which reduce production efficiency and weaken market performance (Changalima & Ismail, 2022; Orr *et al.*, 2018). These challenges underscore the need to identify the key determinants of both the decision to participate and participation intensity among paddy farmers in Iran, with particular attention to high-potential regions.

In addition, farmers often face limited access to information on prices, demand, and marketing methods, coupled with insufficient training in production and sales, which reflects weak institutional support and further raises transaction costs (John Kibara & Balázs Gyula, 2024; Zamanialaei *et al.*, 2022). Taken together, inadequate infrastructure, poor information flow, and rising transaction costs form critical barriers that limit farmers' access to value-added markets and constrain their effective market participation (Changalima & Ismail, 2022; John Kibara & Balázs Gyula, 2024; Mahuwi & Israel, 2023; Renkow *et al.*, 2004).

Rising transaction costs in input markets can limit farmers' access to essential materials such as fertilizers and micronutrients (Ataei *et al.*, 2021; Camara & Alhassane, 2017). (Ismail, 2022) and (Lopera *et al.*, 2023) show that restricted input access reduces yields and weakens farmers' ability to generate marketable surplus, thereby lowering market participation. These constraints are often compounded by gaps in market infrastructure. In many rural areas, limited access to milling facilities, storage infrastructure, and nearby sales centers reduces farmers' marketing options. As (Mosavi & Alipour, 2019) note, farmers may therefore sell unprocessed paddy at relatively low prices to brokers and wholesalers. This infrastructure gap contributes to inefficient marketing chains characterized by multiple intermediaries, higher transport and coordination costs, and limited price transparency, which restricts entry into higher-value rice markets and enables intermediaries to capture a substantial share of margins (Mahuwi & Israel, 2023).

In addition, weak institutional support is reflected in limited access to timely information on prices and demand conditions, as well as insufficient training in production and marketing practices, which further increases transaction costs (John Kibara & Balázs Gyula, 2024; Zamanialaei *et al.*, 2022). Taken together, infrastructure constraints, information gaps, and elevated transaction costs form key barriers that limit farmers' access to value-added markets and reduce effective market participation (Changalima & Ismail, 2022; Renkow *et al.*, 2004). These persistent constraints highlight the importance of analyzing the determinants of paddy market participation and participation intensity in Iran.

Recent studies show that supply chain conditions and related constraints can shape market participation intensity among smallholder farmers in developing countries (Asfaw *et al.*, 2022; Claude *et al.*, 2025; Dey & Singh, 2023; Lopera *et al.*, 2023; Mathenjwa *et al.*, 2025; Mdoda *et al.*, 2024; Morton & Martey, 2021; Ndlovu *et al.*, 2024; Tasila Konja & Mabe, 2023). This evidence indicates that participation decisions are influenced by institutional services, market infrastructure, farm assets, and demographic and human capital characteristics (Lopera *et al.*, 2023; Ndlovu *et al.*, 2024). The influence of these factors can differ across products and regions because transaction costs, market organization, price incentives, and access to processing and information systems are context-specific and vary with commodity characteristics and local institutional arrangements. Despite the critical role of paddy cultivation in supporting rural livelihoods in Iran, limited attention has been given to the constraints that restrict farmers' participation in paddy markets. In particular, evidence remains scarce for high-potential regions such as Golestan Province. To address this gap, the present study examines key determinants of both participation and participation intensity by considering market structure, institutional access, production inputs, and farmer characteristics related to assets and human capital. The findings are intended to inform policy and institutional measures that reduce transaction costs, strengthen market infrastructure and information systems, and support technology and input access to improve farmers' linkage to higher-value markets.

This study also addresses methodological challenges in modeling market participation as a two-stage decision process. Farmers first decide whether to participate in the paddy market, and conditional on participation, they determine the share of output marketed as paddy (Ellemare & Arrett, 2006; Holloway *et al*., 2001). Many empirical studies have analyzed these decisions using Tobit, Heckman two-step, or double-hurdle models (Abafita *et al*., 2016; Abu, 2015; Leta, 2018; Morton & Martey, 2021). However, the commercialization index, commonly defined as the ratio of sales to total production, is a fractional variable bounded between 0 and 1 (von Braun & Kennedy, 1994). Conventional linear specifications may generate predictions outside the feasible range, which can distort inference and marginal effect interpretation (Govereh *et al*., 1999; Yen, 2005).

To address these limitations, recent work has adopted fractional regression and related two-part approaches for bounded outcomes (Ndlovu *et al*., 2024; Tasila Konja & Mabe, 2023). Building on this literature, we employ the generalized two-part fractional regression model (GTP-FRM) developed by (Schwiebert & Wagner, 2015). The model consists of a first-stage participation equation and a second-stage fractional regression for participation intensity, and it allows for dependence between the unobserved determinants of the two stages. This feature is particularly relevant in the context of paddy farmers in Golestan Province, where participation and the share of output sold as raw paddy may be jointly influenced by unobserved constraints such as access to services, market connectivity, and post-harvest capacity. For robustness, we also compare the results with estimates from the Heckman two-step approach.

Conceptual Framework

The conceptual framework (Fig. 1) illustrates the variables hypothesized to influence both the decision to participate and the intensity of participation in the paddy market.

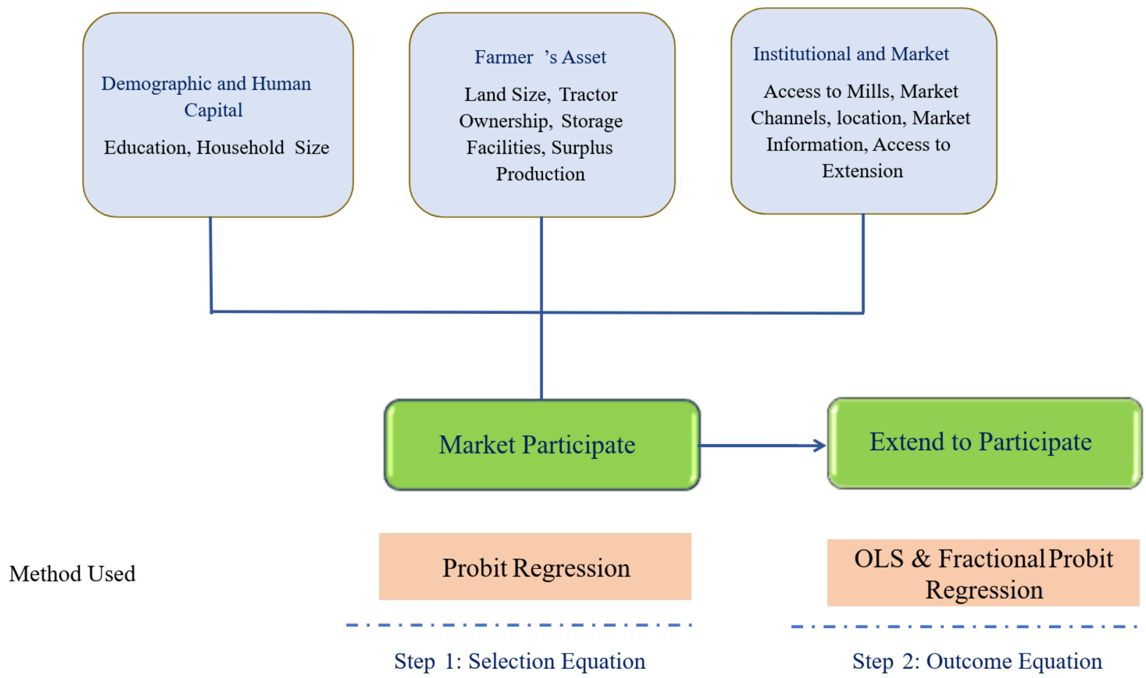

Figure 1- Conceptual framework, Source: Authors' construct

In this study, market participation is modeled as a two-stage process. The first stage, referred to as the decision to participate, captures whether a farmer sells raw paddy in the market (1 = participates, 0 = does not participate). The second stage measures participation intensity through the market participation index, defined as the share of the gross value of paddy production that is sold as unprocessed paddy. This index is a fractional variable bounded between 0 and 1, reflecting the proportion of output commercialized in raw form.

To avoid overfitting, mitigate multicollinearity, and identify the most relevant predictors, the LASSO (Least Absolute Shrinkage and Selection Operator) method was employed for variable selection (Ogundimu, 2022). The selected explanatory variables are grouped into three conceptual categories: demographic and human capital factors (e.g., education level and household size), farmer assets (e.g., cultivated area, storage facilities, Tractor Ownership) and institutional and market factors (e.g., access to milling services, market information, marketing channels, and location). Table A1 in the Appendix provides detailed definitions and measurement scales for all variables. For example, household size reflects the total number of household members.

To estimate the determinants of participation, a probit regression is applied in the first stage to model the binary decision to participate. In the second stage, different estimation strategies are employed depending on the modeling approach. Under the Heckman two-stage model, ordinary least squares (OLS) is used to estimate participation intensity conditional on participation. However, because the participation index is a bounded fractional outcome, OLS may generate predictions outside the feasible range and lead to biased marginal effects. To address this limitation, the generalized two-part fractional regression model (GTP-FRM) is employed. In this framework, the first stage models the participation decision, and the second stage applies a fractional probit specification to the bounded participation index. This approach ensures that predicted values lie within the unit interval and allows for dependence between the participation decision and participation intensity, thereby providing a more consistent and theoretically appropriate estimation strategy for fractional commercialization measures. For comparison and robustness, results from the Heckman model are also reported.

Theoretical Framework and Hypotheses

In deciding about market participation and the level of supply, paddy producers act as economic agents with bounded rationality who seek to maximize utility (Jijue *et al.*, 2024). These decisions occur sequentially under the influence of several factors (Goetz, 1992; John Kibara & Balázs Gyula, 2024; Key *et al.*, 2000). Farmers first decide whether to participate in the market and then determine the volume of sales. Identifying the determinants of these decisions can be understood through the lenses of transaction cost theory (Key *et al.*, 2000; Omamo, 1998), market transition theory (Nee, 1989), and access theory (Ribot & Peluso, 2003). Within the transaction cost framework, which derives from the New Institutional Economics, farmers' market participation is associated with costs of exchange that depend on institutional efficiency (John Kibara & Balázs Gyula, 2024; Renkow *et al.*, 2004). Lower transaction costs therefore increase the likelihood of market participation (Changalima & Ismail, 2022; John Kibara & Balázs Gyula, 2024).

According to market transition theory, economic reforms and improved infrastructure create new opportunities and incentives for farmers to engage in markets (Ismail, 2014; Nee, 1989). Similarly, access theory emphasizes that the ability to benefit from market opportunities depends on supply chain support systems, cost-efficiency, and the presence of enabling structures and processes (Ribot & Peluso, 2003). Elements such as transport infrastructure, distribution strategies, and product quality also affect these conditions and can enhance farmer participation (Mahuwi & Israel, 2023).

Overall, integrating these three theoretical frameworks provides a comprehensive analytical perspective, as no single approach can fully capture the complex interactions shaping farmers' participation decisions (Hagos *et al.*, 2020; Hlatshwayo *et al.*, 2021). In the specific context of Golestan province, where paddy production is characterized by smallholder dominance, spatial dispersion of farms, reliance on intermediary-based marketing channels, and uneven access to storage and processing facilities, these theoretical perspectives are particularly relevant for explaining both market entry decisions and participation intensity. Based on this integrated framework and the institutional and structural characteristics of Golestan province, the study develops a set of empirically testable hypotheses to examine the determinants of paddy market participation.

Consistent with the conceptual structure illustrated in Figure 1, the hypotheses are organized into three thematic groups reflecting the core dimensions of the analytical framework, namely farmer assets, institutional and market access factors, and demographic and human capital characteristics. This structured presentation maintains conceptual coherence while allowing each determinant to be tested separately. The complete set of operationalized and disaggregated hypotheses (H1a–H11b) is provided in Appendix A.

CH1: Farmers' Assets

Drawing on transaction cost theory, farmers' assets including land size, tractor ownership, storage facilities and surplus production influence production capacity, liquidity, and the ability to bear exchange costs in market transactions (Changalima & Ismail, 2022). In Golestan Province, where access to machinery and storage infrastructure varies considerably across farmers, differences in asset ownership are expected to shape both the probability and intensity of participation in the paddy market.

CH1: In Golestan Province, farmers' assets including land size, tractor ownership, storage facilities and surplus production are significantly associated with participation probability and participation intensity in the paddy market.

CH2: Institutional and Market Access Factors

Drawing on access theory, market transition theory, and transaction cost theory, farmers' participation decisions are shaped not only by their internal resource capacity but also by the institutional and market environment in which they operate (Renkow *et al.*, 2004; Ribot & Peluso, 2003). Institutional mechanisms such as milling services, extension support, and access to market information influence farmers' ability to reduce transaction costs, interpret price signals, and coordinate with buyers (Kyaw *et al.*, 2018; Morton & Martey, 2021; Ogbaro *et al.*, 2022).

According to market access and transaction cost theories, geographic distance from markets and transportation costs are key constraints on farmers' direct market access (Mahuwi & Israel, 2023). In rural areas, limited processing facilities and weak transport infrastructure increase marketing costs and often compel farmers to sell through intermediaries (Andaregie *et al.*, 2021; Changalima & Ismail, 2022). In Golestan Province, many paddy producers reside in rural villages located at considerable distances from urban markets and processing centers. Consequently, farm location, defined in this study as residence in rural versus more centrally connected areas, together with differences in marketing channels such as sales to consumers, millers, wholesalers, or brokers, may significantly influence both participation probability and participation intensity.

CH2: In Golestan Province, institutional and market factors, including access to mills, marketing channels, location, access to market information, and extension services, are significantly associated with participation probability and participation intensity in the paddy market.

CH3: Demographic and Human Capital Factors

Drawing on transaction cost theory and human capital theory, individual and household characteristics influence farmers' productivity, decision-making capacity, and engagement with markets (Baiyegunhi, 2024; Osmani & Hossain, 2015). Education may reduce transaction costs by improving farmers' ability to interpret market information, adopt improved technologies, and coordinate with buyers (John Kibara & Balázs Gyula, 2024;

Olwande & Mathenge, 2012). However, in contexts where processing facilities are available, more educated farmers may shift toward value addition through rice marketing rather than direct paddy sales (Denis Ruhinduka *et al.*, 2020).

Household size may also shape commercialization patterns. Larger households may increase labor availability and production capacity, yet their higher consumption needs may reduce marketable surplus (Changalima & Ismail, 2022; Khun & Lim, 2023; Mdoda *et al.*, 2024). In Golestan Province, where farm households vary considerably in demographic structure and human capital characteristics, these differences may influence both participation probability and participation intensity in the paddy market.

CH3: In Golestan Province, demographic and human capital factors, including education and household size, are significantly associated with participation probability and participation intensity in the paddy market.

Methodology

Study Area

The study was conducted in Golestan Province, in northern Iran (36°44′–38°05′ N, 53°53′–56°14′ E), covering an area of approximately 20,000 km². Influenced by the Alborz Mountains, the Caspian Sea, and the plains of Turkmenistan, the province enjoys a diverse climate favorable for agriculture. Golestan's economy relies heavily on crop production, with major crops including wheat, canola, rice, and soybeans (Motevali *et al.*, 2019). The province ranks as Iran's third-largest rice producer, cultivating about 64,000 hectares and yielding nearly 388,000 tons annually. Approximately 20.3% of the farmers grow paddy, with 126 mills processing it into rice.

Data Collection and Sample Size

This study employed a multi-stage cluster random sampling design to select paddy farmers in Golestan Province during the 2023–2024 cropping season. In the first stage, four counties (Azadshahr, Galikesh, Aliabad Katul, and Gorgan) were randomly selected from the 13 paddy-producing counties in the province (Fig. 2). In the subsequent stage, districts, sub-districts, and villages within each selected county were randomly chosen. Finally, paddy farmers within the selected villages were randomly selected and surveyed using structured questionnaires.

A preliminary survey was conducted in the four randomly selected counties, with 20 questionnaires collected from each county (80 observations in total). Based on operational considerations and proportional allocation across counties, the final sample size was set at 150 respondents. This sample size is consistent with similar empirical studies on smallholder market participation in developing countries, which commonly rely on samples ranging from approximately 140 to 180 observations (e.g.,(Hagos *et al.*, 2020; Tarekegn & Shitaye, 2022)).

Analytical Method

The market participation extent of paddy farmers was calculated using the market participation index (MPI) approach. The MPI approach, as proposed by (Govereh *et al.*, 1999) and (Strasberg *et al.*, 1999), is utilized in a modified form to determine an index quantifying the market participation intensity of paddy farmers. The paddy market participation index (*PMPI*) in eq (1). calculates the ratio of the gross value of paddy sales by i^{th} farmer in j^{th} year (j= 2023 farming season) to the gross value of all paddy produced by the same i^{th} farmer in that j^{th} year.

$$PMPI_{ij} = \frac{Gross\ value\ of\ paddy\ sale_{ij}}{Gross\ value\ of\ all\ paddy\ production_{ij}} \qquad (1)$$

Figure 2- Geographical location of the study area (Golestan Province) in Iran

This measure complements the two-stage framework adopted in this study, in which the first stage models the probability of participation and the second stage evaluates the extent of participation (H1–H18). By providing a continuous indicator of commercialization intensity, the MPI enables a more detailed assessment of variation in market engagement among farmers. Research conducted by (Morton & Martey, 2021; Ndlovu *et al*., 2024; Tasila Konja & Mabe, 2023) employed this indicator to assess the extent of farmers' participation in markets.

The market participation index of paddy is calculated as the proportion of paddy sold relative to total paddy produced. Consequently, a fractional response variable arrives, providing the condition $0 \le PMPI_i \le 1$, where $PMPI_i = 0$ indicates that a paddy farmer does not engage in the market. Consequently, considering θ and a vector x comprising k covariates intended to explain the dependent variable, the emphasis is on estimating the mean response of *PMPI*, thereby estimating $E(PMPI \mid x)$. As the consequence, the linear specification $E(PMPI \mid x) = \theta$ becomes inconsistent, as it presumes a linear influence of explanatory variables on the predicted value of *PMPI*, potentially leading to predicted values outside of the limits [0, 1], and might produce nonsensical results, without valid interpretation, including that of the marginal effects (Faria *et al*., 2020).

Paddy market participation is viewed as a sequential decision-making process. In the first stage, farmers decide whether to supply paddy to the market, and in the second stage, those who participate determine the intensity of their participation. Estimating participation intensity using only market participants may lead to sample selection bias, since this group is not randomly drawn from the full farming population. If unobserved factors affect both the participation decision and sales intensity, results based only on participants cannot be generalized to all farmers. To address this issue, (Heckman, 1979) introduced the sample selection model, expressed as follows:

The model consists of two equations: a selection equation that models the participation decision, and an outcome equation that models participation intensity conditional on selection.

$PMPI_i^* = x_i'\beta + u_i;$	Outcome equation (participation intensity)	(2)
$s_i = 1(w_i'\gamma + \varepsilon_i > 0);$	Selection equation (participation decision)	(3)

$$PMPI_i = s_i PMPI_i^* \qquad (4)$$

Where x_i' denotes the explanatory observed variables influencing the latent outcome $PMPI_i^*$ and defines the error term in the regression Eq. (2). s_i represents the selection equation, in this study, an observed binary variable showing a farmer's participation in the paddy market ($s_i = 1$) or non-participation ($s_i = 0$), with independent variables given by w_i', whereas ε_i is the error term of the selection Eq.(3). Both u_i and ε_i , which are assumed to follow a conditional bivariate normal distribution, capture the aggregated effects of the unobserved components in this model. They are expressed as follows:

$$\begin{pmatrix} u_i \\ \varepsilon_i \end{pmatrix} | x_i, w_i \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \rho \\ \rho & 1 \end{pmatrix}\right), \qquad (5)$$

Where ρ is the correlation coefficient between u_i and ε_i . Thus, when $\rho \neq 0$, the estimation might suffer from sample selection bias. The Heckman selection model mitigates bias by calculating and including the inverse Mills' ratio (*IMR*) into the regression equation, hence facilitating unbiased outcomes (Faria et al., 2020).

Studies on the Heckman approach show that collinearity between the correction term and independent variables can substantially increase standard errors (Certo *et al.*, 2016; Clougherty *et al.*, 2016). *IMR* is statistically significant, this multicollinearity may distort coefficient estimates (Bushway *et al.*, 2007). This problem is exacerbated in the absence of exclusion restrictions, that is, variables that affect the selection equation but do not directly enter the outcome equation. Therefore, the Heckman model should include at least one variable in the first stage that is excluded from the second stage (Bushway *et al.*, 2007; Sartori, 2003). Including such restrictions reduces the correlation between the correction term and explanatory variables, improving model robustness. (Bushway *et al.*, 2007; Hoq *et al.*, 2021). Scholars agree that models with exclusion restrictions yield more reliable results, and the correlation between *w* and *IMR* can assess their strength (Bushway *et al.*, 2007; Certo *et al.*, 2016; Kennedy, 2008; Leung & Yu, 1996).

The main limitation of the Heckman sample selection model is that the regression equation (Eq. (2)) assumes a linear relationship between the regressors and the dependent variable, which may generate predicted values [0, 1] interval. Moreover, the model relies on the assumption of joint normality of the error terms in the selection and outcome equations and fails to capture unobserved individual-specific effects, which may lead to biased estimates and complicate interpretation (Faria *et al.*, 2020). Tobit models are sometimes used as an alternative; however, they are appropriate only when the dependent variable is censored at both lower and upper bounds, typically between 0 and 1. In most cases, boundary observations arise from selection mechanisms rather than true censoring. Furthermore, the Tobit specification also assumes normality and homoscedasticity of the dependent variable, which may not hold in practice (Faria *et al.*, 2020; Ramalho *et al.*, 2011).

To address these limitations, a fractional dependent variable (FDV) should be estimated using a different econometric method, providing that $E(PMPI \mid x)$ remains inside the valid interval [0,1], and that the estimation provides consistent and unbiased outcomes.

To address these issues, (Ramalho & da Silva, 2009) proposed the two-part fractional regression model (TP-FRM), which applies a binary specification to model the participation decision (whether to participate or not) and a fractional specification to model participation intensity, measured as the proportion of output sold. However, if the two decisions are interdependent, the model may suffer from selection bias, since unobserved factors influencing the participation decision may also affect the intensity decision, similar to the sample selection problem in the Heckman framework (Wulff, 2019). To overcome this limitation, (Schwiebert & Wagner, 2015) introduced the generalized two-part fractional regression model (GTP-FRM), which explicitly models the correlation between participation and intensity decisions. The GTP-FRM therefore generalizes the TP-FRM by allowing for dependence between the two stages, while the TP-FRM can be viewed as a restricted special case that assumes independence between them.

The estimation of the generalized two-step fractional regression model of (Schwiebert & Wagner, 2015) for the decision equation (s_i) is as follows.

$$s_i = 1(w_i'\gamma + \varepsilon_i > 0); \tag{6}$$

Therefore, an observation (i) has a non-zero outcome if and only if $w_i'\gamma + \varepsilon_i > 0$. For simplicity, it is assumed that the error term u follows a standard normal distribution, indicating that

$$\Pr(s_i = 1 | w_i) = \Phi(w_i'\gamma) \tag{7}$$

where $\Phi(.)$ denotes the standard normal cumulative distribution function. For the participation intensity equation in the paddy market, the conditional mean is determined as follows:

$$\begin{gathered} E(PMPI_i | x_i, w_i, s_i = 0) \\ E(PMPI_i | x_i, w_i, s_i = 1) = \frac{\Phi_2(x'\beta, w'\gamma : \rho)}{\Phi(x'\beta)} = \frac{\Phi_2(\beta_0 + \beta_1 x_i, \gamma_1 w_{i1} + \gamma_2 w_{i2}; \rho)}{\Phi(\gamma_0 + \gamma_1 w_{i1} + \gamma_2 w_{i2})} \end{gathered} \tag{8}$$

$\Phi_2(.)$ represents the bivariate standard normal distribution, with ρ denoting the correlation between participation and intensity decisions. Eq (8) is the fractional probit specification employed to simulate model nonzero values of *PMPI*.

If $\rho = 0$, the two processes in Eq (2) are independent, so the GTP-FRM simplifies to the TP-FRM, where $E(PMPI | x, w, s = 1) = \Phi(x'\beta)$. Nonetheless, if ρ > 0, the TP-FRM is specified incorrectly.

The GTP-FRM allows both x and w to influence the intensity decision. while x exerts a direct effect, w affects intensity indirectly through the participation equation (Schwiebert & Wagner, 2015). This additional complexity implies that the GTP-FRM requires an exclusion restriction for proper identification of the model. Specifically, at least one variable should affect the decision to participate in the paddy market without directly influencing the extent of participation. Such exclusion restrictions are necessary to ensure credible identification and to reduce potential collinearity between the correction term and the regressors in the second stage, which may otherwise inflate standard errors and bias the estimates(Bushway *et al*., 2007; Certo *et al*., 2016; Sartori, 2003; Wulff, 2019). In the absence of exclusion restrictions, the predicted correction component may be highly correlated with the explanatory variables in the outcome equation, weakening the robustness of the estimates (Hoq *et al*., 2021). Accordingly, in equation 7, $x_i = w_{i1}$ for all i= 1, 2, …, n. while w_{i2} is excluded from the second process and serves as the identifying restriction required for consistent estimation of the model (Schwiebert & Wagner, 2015).

The extended two-part model can be estimated using quasi maximum likelihood (QML). The log-likelihood function is expressed as:

$$\begin{aligned} &\log L(\theta) = \sum_{i=1}^{n} l_i(\theta) \equiv \\ &\sum_{i=1}^{n} \{(1 - s_i)\log(1 - \Phi(w_i'\gamma)) + s_i \log \Phi(w_i'\gamma) \\ &+ s_i \left[\begin{array}{l} (1 - PMPI_i)\log\left(1 - \dfrac{\Phi_2(x'\beta, w'\gamma : \rho)}{\Phi(x'\beta)}\right) \\ + PMPI_i \log \dfrac{\Phi_2(x'\beta, w'\gamma : \rho)}{\Phi(x'\beta)} \end{array} \right] \} \end{aligned} \tag{9}$$

where $\theta = (\beta', \gamma', \rho)'$ denotes the parameter vector to be estimated. Also, the conditional mixed processes approach was used to estimate the generalized bipartite fraction model in Stata (Wulff, 2019).

In ordinary binary probit and fractional probit models, the estimated coefficients represent changes in the underlying latent index rather than direct changes in predicted probabilities. Because the relationship between the regressors and the probability is nonlinear, the coefficients cannot be interpreted directly in probability terms (Wulff, 2019). Therefore, marginal effects are computed to obtain meaningful interpretations in terms of changes in the probability of participation and the expected proportion of output sold. For the GTP-FRM model, the marginal effects of the variable x_k are calculated as follows:

$$E[PMPI_i \mid x_i, w_i] = \Pr(s_i = 0 \mid w_i)$$
$$E[PMPI_i \mid x_i, w_i, s_i = 0] + \Pr(s_i = 1 \mid w_i)$$
$$E[PMPI_i \mid x_i, w_i, s_i = 1] = 0 + \Phi_2(x_i'\beta, w_i'\gamma : \rho) \quad (10)$$

due to a small change in x_k. Consequently, the marginal effect is expressed as:

$$\frac{\partial E[PMPI_i \mid x_i, w_i]}{\partial x_k} = \frac{\partial \Phi_2(x_i'\beta, w_i'\gamma : \rho)}{\partial x_k} \quad (11)$$

For a specific individual *i*, where x_k may be present in both x and w. The average marginal effect is calculated as:

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial \Phi_2(x_i'\beta, w_i'\gamma : \rho)}{\partial x_k}, \quad (12)$$

which is simply the marginal effect averaged over all individuals (Schwiebert & Wagner, 2015; Wulff, 2019).

Therefore, the marginal effects of the explanatory variables are computed as follows: Equation (13) defines the marginal effects on the probability of participation in the paddy market, while Equation (14) specifies the marginal effects on the conditional mean of participation intensity. These expressions allow for an interpretable assessment of how changes in explanatory variables affect both stages of market participation (Diakité *et al.*, 2025; Schwiebert & Wagner, 2015; Wulff, 2019).

$$\frac{\partial \Pr(s_i = 1 \mid w_i)}{\partial w_k} \quad (13)$$

$$\frac{\partial E(PMPI_i \mid x, w, s = 1)}{\partial x_k} \quad (14)$$

Before starting the analysis, the assumption of collinearity and examination of the omitted variable and functional form were performed using the variance inflation factor (VIF) and Ramsey tests, respectively (Ramalho *et al.*, 2011; Wulff, 2019).

All estimations were performed using Stata 17. To further address the risk of overfitting and multicollinearity, and to systematically select the most relevant predictors for the participation decision, we employed the Least Absolute Shrinkage and Selection Operator (LASSO) prior to the main two-part model. Given the binary nature of the dependent variable in the selection equation, a probit LASSO was applied. The tuning parameter λ (lambda), which determines the strength of the penalty, was chosen by 10-fold cross-validation minimizing the cross-validated deviance. This procedure automatically shrinks the coefficients of irrelevant variables exactly to zero. At the optimal λ (0.018), 15 out of 21 candidate variables retained non-zero coefficients and were subsequently used as predictors in the estimation of both the two-stage Heckman model and the generalized two-part fractional regression. A detailed list of all candidate variables, their LASSO selection status, and standardized coefficients is provided in Table 1. This data-driven selection helps to preserve degrees of freedom and enhance statistical power in the subsequent non-linear multivariate analysis.

Empirical Results and Discussion

Descriptive Analysis

Table 2 provides a descriptive summary of the independent variables influencing farmers' participation in the paddy market, based on frequency distribution and chi-square analyses. Out of 150 respondents, 64% were active market participants.

Several binary factors, such as vehicle ownership, access to milling and storage facilities and extension contact, exhibited significant effects on market participation. Additionally, education level, cultivated land area, and market channel showed statistically significant differences at the 1% level. According to Table 3, the average market participation intensity among all farmers was 49%, while for active participants it reached 77%, suggesting that these farmers sold more than half of their total paddy production.

Table 1- Definition of variables and LASSO selection results

Variable name	Definition	LASSO coefficient (Standardized)
Dependent variable		
Market participation	Dummy: 1 if the farmers participate in the Paddy market, 0 otherwise	-
Paddy market participation index (PMPI)	Continuous: Gross value of paddy sold to gross value of all paddy production	-
Independent variable		
Land Ownership	1 If the farmer owns the land, 0 otherwise	-
Farm size		
Small scale	1= If the farm is less than three hectares	
Medium scale	2= If the farm is more than three and less than ten hectares	0.553
Large scale	3= If the farm is more than ten hectares.	
		0.075
tractor ownership	1 If the farmer owns the tractor, 0 otherwise	-0.015
non-farm income	1 If the farmer is engaged in a non-agricultural activity, 0 otherwise	-
Market surplus	The amount of surplus production (1000 tons)	0.931
Storage facilities	1 if the farmer has storage facilities, 0 otherwise	-0.136
Access to mill	1 if the farmer has access to a mill, 0 otherwise	-1.248
Market channels		
Consumer	1= Final consumer Buyer	
Miller	2= Mill Buyer	0.335
Wholesaler	3= Wholesale Buyer	0.163
Broker	4= Broker Buyer	0.921
Location	1 if the farmer lives in the village, 0 otherwise	0.322
Extension services	1 if the farmer has contacted the extension services, 0 otherwise	0.080
Market information	1 if farmer has access to market information, 0 otherwise	0.256
Access to fertilizer	1 if the farmer has access to fertilizer, 0 otherwise	-
Paddy variety	1 If the farmer grows a local variety of paddy, 0 otherwise	-
Age	Farmer age (year)	-
Education		
Below the diploma	1= Farmer with a degree below a diploma	
Diploma	2= Farmer with a diploma	-0.189
Bachelor or Above Bachelor	3= Farmer with a bachelor's or above a bachelor's degree	-0.138
Experience	Farming experience Number (year)	-
Household size	Household size of farmer	-0.171

Model Specification with Exclusion Restriction

This study employed the Heckman two-step model and the generalized two-part fractional regression to identify factors affecting farmers' participation decisions and the intensity of market involvement. Prior to estimation, appropriate exclusion restrictions for the outcome equation were identified following (Hoq *et al.*, 2021), taking into account multicollinearity diagnostics, correlations among explanatory variables, and the properties of the correction term. In the Heckman framework, a first-stage probit model was estimated to analyze the participation decision. The Inverse Mills Ratio (IMR) was then derived from the first-stage probit and included in the second-stage regression to correct for potential selection bias. Multicollinearity and correlations between the IMR and the explanatory variables were assessed using the Variance Inflation Factor (VIF) and pairwise correlation coefficients. In applied econometrics, a VIF below 5 and a correlation coefficient below 0.5 are commonly used benchmarks to indicate acceptable levels of multicollinearity (Hoq *et al.*, 2021; Kim, 2019). As reported in Table 4, the VIF for the IMR was 9.50, indicating potential multicollinearity concerns between the IMR and certain explanatory variables.

Table 2- Disaggregated descriptive statistics of market participation decision for classified variables

Variables	Category	Not Participated 54(36)	Participated 96 (64)	Total 150 (100)	Chi-square value
		Market participation decision			
Education	Below the diploma	25(46.3)	23(24)	48(32)	8.881**
	Diploma	11(20.3)	36(37.5)	47(31.3)	
	Bachelor or Above Bachelor	18(33.3)	37(38.5)	55(36.6)	
Farm size	Small scale	45(83.3)	41(42.7)	86(57.3)	23.445***
	Medium scale	6(11.1)	41(42.7)	47(31.3)	
	Large scale	3(5.6)	14(14.6)	17(11.4)	
Tractor ownership	No	28(51.9)	26(27)	54(36)	9.202***
	Yes	26(48.1)	70(73)	96(64)	
Storage facilities	No	12(22.2)	63(65.7)	75(50)	26.041***
	Yes	42(77.8)	33(34.3)	75(50)	
Access to mill	No	12(22.2)	71(74)	83(55.3)	37.427***
	Yes	42(77.8)	25(26)	67(44.7)	
Market channel	Consumer	23(42.6)	2(2)	25(16.7)	53.432***
	Miller	4(7.4)	16(16.7)	20(13.3)	
	Wholesaler	2(3.7)	28(29.2)	30(20)	
	Broker	16(29.6)	50(52.1)	66(44)	
Location	City	18(33.3)	34(35.4)	52(34.6)	0.066
	Village	36(66.6)	62(64.6)	98(65.4)	
Extension services	No	31(57.4)	35(36.5)	66(44)	6.155*
	Yes	23(42.6)	61(63.5)	84(56)	
Market information	No	8(14.8)	7(7.3)	15(10)	2.173
	Yes	46(85.2)	89(92.7)	135(90)	

Note: The value in parentheses is the percentage of frequency, (***, **, * indicates the 1%, 5% and 10% levels of significance)

Table 3- Market participation decision with continuous independent variables

	Market participated decision						
	Participated		**Not Participated**		**t-value**	**Total**	
Variables	**Mean**	**Sta. Dev**	**Mean**	**Sta. Dev**		**Mean**	**Sta. Dev**
Market participation index	0.77	0.25	0	0	-21.85***	0.49	0.42
Household size	3.74	1.24	4.47	1.73	2.90***	4.01	1.48
Market surplus	29.52	30.92	6.98	14.03	5.06***	21.41	28.24

(***, **, * indicates the 1%, 5% and 10% levels of significance)

Fig. 3 shows that the variables related to storage facilities (0.625) and access to milling services (0.716) have the highest correlations with the IMR among all explanatory variables. As stated in Table 4, excluding these variables reduced the VIF from 9.50 to 2.48, confirming their strong correlation with other predictors and improving the model's specification.

Access to milling services influences the decision to participate in the market, as farmers with milling capacity usually sell their paddy in processed form (Rice) rather than as paddy (Denis Ruhinduka *et al.*, 2020; Nakazi & Sserunkuuma, 2013).

Table 4- Variance Inflation Matrix (VIF) of the independent variables used in probit model.

Variable name	VIF	
	Before of exclusion restriction	After of exclusion restriction
Diploma	1.81	1.77
Bachelor	2.14	2.08
Household size	1.18	1.17
Medium scale	1.94	1.67
Large scale	3.79	3.45
Tractor ownership	1.56	1.55
Market surplus	3.71	3.47
Storage facilities	2.75	-
Access to mill	8.23	-
Miller	4.48	2.47
Wholesaler	3.57	3.46
Broker	3.42	3.26
Location	1.36	1.23
Extension services	1.50	1.48
Market information	1.46	1.24
IMR	9.50	2.48
Mean VIF	3.27	2.20

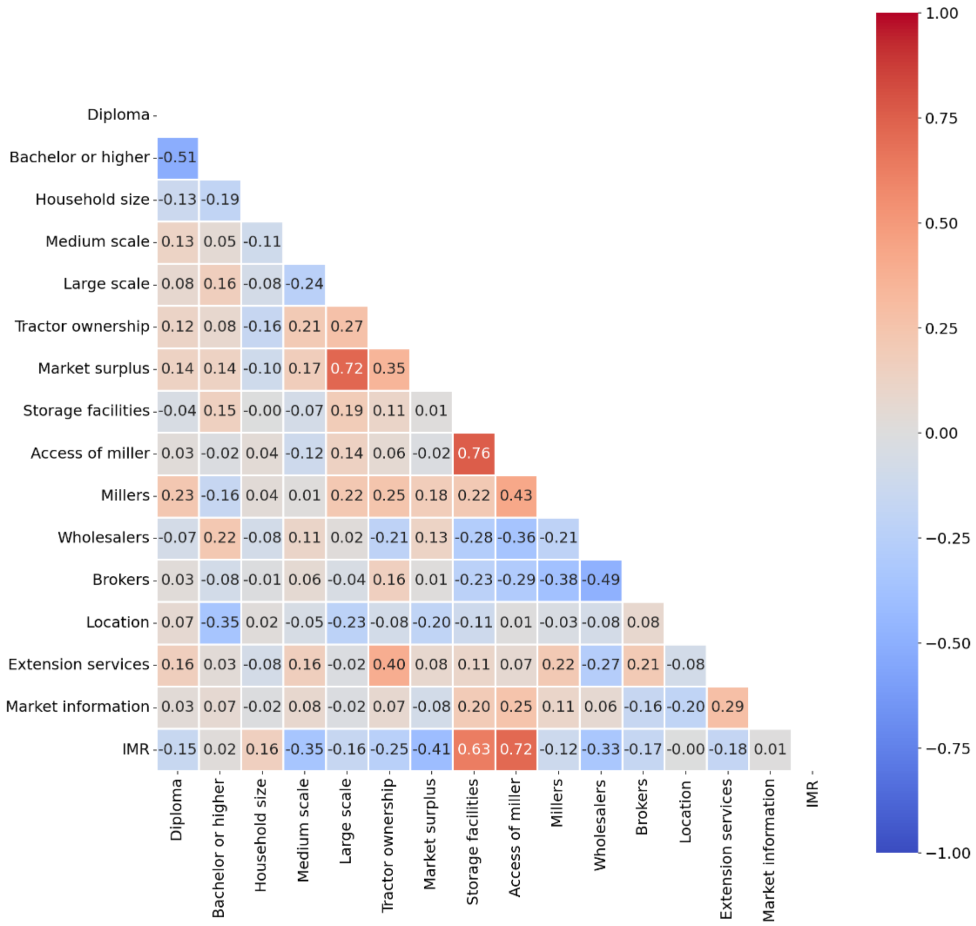

Figure 3- Heatmap of the correlation matrix of explanatory variables

Likewise, access to storage facilities primarily affects participation decisions by allowing farmers to store processed rice and sell it later during favorable market conditions (Dey & Singh, 2023). For these reasons, both variables were excluded from the second stage of estimation in both models.

Table 5 presents the estimation results of the Heckman two-step and GTP-FRM models. The Wald statistics for both models are statistically significant at the 1% level, indicating the joint significance of the explanatory variables and confirming that the models are properly specified.

Table 5- Estimation results of the two-stage Heckman model and generalized two- part fractional regression

Variable	Heckman's two-step selection model				GTP-FRM			
	Probit		OLS		Probit		Fractional	
	Coef	S. E	Coef	S. E	Coef	S. E	Coef	S. E
Storage facilities	0.155	0.901			0.156	0.579		
Access to mill	-4.419***	1.362			-4.382***	0.923		
Market surplus	0.034*	0.019	0.005***	0.001	0.032**	0.016	0.025***	0.007
Farm size	Small scale is a base category							
Medium scale	1.988**	0.872	-0.141***	0.056	2.029***	0.757	-0.590***	0.196
Large scale	0.663	1.214	-0.428***	0.121	0.685	1.104	-1.813***	0.438
Tractor ownership	-0.126	0.632	0.030*	0.063	-0.159	0.695	0.100**	0.234
Market information	2.561**	1.188	-0.232*	0.129	2.523***	0.953	-2.054***	0.431
Extension services	0.080	0.637	0.188**	0.054	0.122	0.547	0.505***	0.188
Market Channel	Consumer is a base category							
Miller	3.246**	1.392	0.156	0.169	3.257***	0.778	0.411	0.275
Wholesaler	2.847*	1.463	0.203	0.167	2.841***	1.007	0.583*	0.306
Broker	1.379	1.045	0.040	0.158	1.367***	0.518	0.144	0.235
Location	1.181*	0.713	-0.010	0.050	1.144***	0.577	0.010	0.189
Education	Below the diploma is a base category							
Diploma	-1.456	0.909	-0.034	0.061	-1.488**	0.725	-0.130	0.214
Bachelor or Above Bachelor	-1.017	0.897	0.015	0.068	-1.018	0.648	0.069	0.211
Household size	-0.249	0.216	-0.011	0.019	-0.249	0.160	-0.053	0.060
IMR			-0.751**	0.335				
Constant	-1.098	1.394	1.010***	0.269	-1.044**	0.943	2.188	0.361
rho					-0.477**	0.170		
Wald chi2	130.55***				146.54***			
RESET test					0.33		5.58*	

(***, **, * indicates the 1%, 5% and 10% levels of significance)

In the Heckman model, the coefficient of the Inverse Mills Ratio (IMR) is statistically significant at the 5% level, indicating that correcting for selection bias is necessary. In the GTP-FRM model, the estimated correlation coefficient ρ (−0.477) is statistically significant at the 1% level, reflecting dependence between the participation and intensity decisions. These results suggest that unobserved factors simultaneously influence both the decision to participate in the paddy market and the extent of participation, thereby confirming the presence of selection effects and interdependence between the two stages (Regasa Megerssa *et al.*, 2020; Schwiebert & Wagner, 2015).

Although the Heckman model corrects for selection bias, it assumes a linear relationship between the independent variables and the dependent variable in the outcome equation, making it inappropriate for modeling bounded fractional outcomes. As a result, 8 out of 150 predicted values for paddy market participation intensity fall outside the valid range of [0,1]. Predictions outside this admissible interval distort the calculation of average marginal effects, as they violate the bounded nature of the dependent variable and may bias the estimated effects (Faria *et al.*, 2020). In contrast, the GTP-FRM model, provides more stable and consistent estimates, with a larger number of statistically significant variables and stronger effects across both stages. Furthermore, the Ramsey RESET test was applied to assess functional form misspecification. The non-rejection of the null hypothesis for both components of the GTP-FRM at the 5% significance level indicates no evidence of functional form misspecification, thereby supporting the validity of the model specification. Accordingly, the discussion of average marginal effects in the following section focuses on the GTP-FRM results.

Determinants of Participation Decision and Intensity

The average marginal effects (AME) of explanatory variables on the probability and intensity of farmers' participation in the paddy market are presented in Table 6. Results related to farmers' assets indicate farm size positively affects the likelihood of participation. At the 1% significance level, the probability of participation among medium-scale farmers is 17.4% higher than small-scale farmers, supporting hypothesis H1a. However, the effect on participation intensity for medium-scale farmers is only 0.026 points on the fractional intensity scale (bounded between 0 and 1) and is statistically insignificant. Therefore, hypothesis H1b is rejected due to the absence of statistical significance, indicating that farm size does not have a meaningful effect on the share of the gross value of paddy production that is marketed. This suggests that although medium-scale farmers are more likely to enter the market, the value-based share of paddy sold does not differ significantly from that of small-scale farmers. These findings are consistent with previous studies on rice market participation (Lopera *et al*., 2023; Tesfahun *et al*., 2022).

For large-scale farmers, the probability of participation is slightly higher than small-scale farmers; however, their participation intensity is 0.273 points lower and statistically significant at the 1% level, confirming hypothesis H1b. This indicates that although large-scale farmers are more likely to participate, they allocate a smaller share of the gross value of their paddy production to paddy sales. Their lower participation intensity may reflect stronger financial capacity, better access to storage and milling facilities, and reduced transaction costs, which enable them to process paddy and market rice instead of selling paddy directly (Denis Ruhinduka *et al*., 2020).

Table 6- Average marginal effects for decision to participate and intensity of market participation

Variable	Decision to participate (1)		intensity of participation (2)	
	AME[a]	Std. E	CAME[b]	Std. E
Storage facilities	0.013	0.050	0.010	0.037
Access to mill	-0.377***	0.058	-0.280***	0.050
Market surplus	0.003**	0.001	0.006***	0.001
Farm size	Small scale is a base category			
Medium scale	0.174***	0.058	0.026	0.054
Large scale	0.058	0.093	-0.273***	0.093
Tractor ownership	-0.013	0.059	0.007	0.053
Extension	0.010	0.047	0.096**	0.040
Market information	0.217***	0.064	-0.198**	0.098
Market Channel	Consumer is a base category			
Miller	0.280***	0.069	0.280***	0.066
Wholesaler	0.244***	0.087	0.284***	0.080
Broker	0.117**	0.049	0.113**	0.054
Location	0.098**	0.042	0.075*	0.042
Education	Below the diploma is a base category			
Diploma	-0.128*	0.068	-0.118**	0.059
Bachelor or Above Bachelor	-0.087*	0.058	-0.053	0.054
Household size	-0.021	0.013	-0.025*	0.013

Note: [a] Reporting average marginal effects, [b] Reporting average marginal effects conditional, (***, **, * indicates the 1%, 5% and 10% levels of significance).

The volume of marketable surplus has a positive and statistically significant effect on the likelihood of participation in the paddy market at the 5% level, confirming hypothesis H3a. Specifically, a 1% increase in marketable surplus is associated with an increase in the probability of participation of approximately 0.3 percentage points. More importantly, the positive and statistically significant effect indicates that higher paddy productivity strengthens farmers' engagement in the market.

Similar evidence is reported by (Morton & Martey, 2021) for rice farmers. Among participants, the average marginal effects show that a 1 percent increase in surplus leads to a 0.6% rise in participation intensity, confirming hypothesis H3b at the 1% level. This result aligns with findings by (Kyaw *et al.*, 2018; Morton & Martey, 2021; Reyes *et al.*, 2012), who argue that higher rice output generates larger surpluses, encouraging stronger market participation.

According to Table 6, institutional and market variables such as access to mills, market channels, location, and market information significantly influence farmers' participation in the paddy market. Access to mills has a negative and statistically significant effect at the 1% level, confirming hypothesis H5a. Specifically, farmers with access to milling services are 37.7% less likely to sell paddy, as they prefer to process it into rice and sell it at a higher price. This finding is consistent with (Denis Ruhinduka *et al.*, 2020), who reported that distance to mills significantly affects farmers' decisions on whether to market their output as paddy or as rice.

Access to extension services shows no statistically significant effect on the probability of participation in the paddy market, leading to the rejection of H6a due to the absence of statistical significance in the participation decision equation. However, conditional on participation, access to extension services has a positive and statistically significant effect on participation intensity at the 5% level, with a coefficient of 0.096, thereby confirming H6b. This positive effect suggests that access to extension services improves production and market engagement by increasing awareness of input markets, modern practices, high-yielding varieties, and weather conditions. Similar findings were observed by (Abdullah *et al.*, 2019; Maesela *et al.*, 2023; Mathenjwa *et al.*, 2025), who also report that access to extension services improves production performance and consequently increases the intensity of market participation.

Access to market information has a positive and statistically significant effect on the probability of farmers participating in the paddy market at the 1% level, confirming hypothesis H7a. Improved access to information increases the likelihood of participation by 21.7%, as farmers use data on prices, buyers, and demand to reduce transaction costs and plan sales more effectively (Dlamini & Huang, 2019). However, access to market information has a significant negative effect on participation intensity at the 5% level, leading to the rejection of H7b. A one-unit increase in access reduces participation intensity by 0.19 points on the fractional intensity scale. This suggests that informed farmers, aware of price differences, are more likely to process and sell rice when milling facilities are available (Kyaw *et al.*, 2018; Tesfahun *et al.*, 2022). Overall, these findings are consistent with prior studies confirming that access to market information improves farmers' ability to engage strategically in agricultural markets (Claude *et al.*, 2025; Dey & Singh, 2023; Gebre & Deshmukh, 2024; Regasa Megerssa *et al.*, 2020).

Selling to wholesalers, mills, or brokers rather than directly to retailers or consumers significantly increases the probability of participating in the paddy market at the 1% level, confirming hypothesis H8a. Specifically, sales to millers, wholesalers, and brokers raise the likelihood of participation by 28%, 24.4%, and 11.7%, respectively. Among participating farmers, these channels also enhance the intensity of market participation by 28%, 28.4%, and 11.3%, respectively, confirming hypothesis H8b. These findings suggest that intermediaries such as wholesalers and brokers play a crucial role in facilitating market access, as they primarily purchase unprocessed paddy and possess stronger bargaining power and negotiation capacity. The predominance of paddy producers in rural areas, far from urban markets and processing centers, combined with high transaction costs, discourages direct sales to retailers and consumers. Similar conclusions are reported by (Changalima & Ismail, 2022; Mahuwi & Israel, 2023; Zhang *et al.*, 2019), who emphasize that reliance on intermediaries reflects structural limitations and cost barriers within the marketing chain.

Location has a positive and statistically significant effect on the probability of farmers participating in the paddy market at the 5% level, confirming hypothesis H9a. The probability of participation for rural farmers is 0.098 higher than for urban farmers. Furthermore, location has a positive and statistically significant effect on the intensity of paddy market participation at the 10% significance level, with a coefficient of 0.075. Since the dependent variable in this model specifically captures participation in the paddy market, that is, the sale of raw paddy rather than processed rice, this result suggests that rural producers, who are typically located farther from modern processing facilities and face higher transaction costs, are more likely to sell their output as paddy at the farm gate to brokers and wholesalers. This finding aligns with previous studies showing that greater market distance reduces direct participation, as reported for rice by (Hoq *et al.*, 2021) and for vegetables by (Gebre & Deshmukh, 2024). Similarly, (Mathenjwa *et al.*, 2025) found that long travel distances discourage rural producers from accessing markets due to high transportation costs.

Among human capital factors, education level significantly influences the probability of participation in the paddy market. As shown in Table 6, higher education levels are associated with a decline in participation probability at the 10% level, confirming hypothesis H10a. Specifically, farmers with a high school diploma and a bachelor's degree are 12.8 and 8.7% less likely to participate compared with those having less than a diploma. Conditional marginal effects further indicate that, among participants, education negatively affects participation intensity, confirming hypothesis H10b. Farmers with a diploma exhibit 11.8 percentage points lower intensity, while those with a bachelor's degree also show reduced participation.

These results align with findings by (Musah, 2013) for maize and (Abdullah *et al.*, 2019) for rice. Higher education improves farmers' knowledge and adoption of modern technologies (Asfaw *et al.*, 2022; Regasa Megerssa *et al.*, 2020), enhancing productivity and enabling more diversified marketing strategies. Educated farmers, aware of price differentials and market dynamics, often process and sell part of their produce as rice when milling facilities are available, thereby reducing their participation in the paddy market. A similar negative association between education and market participation was also reported by (Worku *et al.*, 2021) with chickpea producers.

Household size shows no statistically significant effect on the probability of participation, leading to the rejection of H11a. Due to the absence of statistical significance in the participation decision equation. However, conditional on participation, household size has a negative and statistically significant effect on participation intensity at the 10% level, thereby confirming H11b. Specifically, each additional household member reduces participation intensity by approximately 2.5 ٪ points. Larger families tend to allocate a greater share of production to household consumption, which reduces the marketable surplus. Moreover, the availability of additional family labor provides labor capacity that facilitates rice processing and marketing, thereby reducing paddy sales and lowering participation intensity in the paddy market. Similar findings were observed by (Kyaw et al., 2018; Regasa Megerssa et al., 2020), who observed that higher household consumption lowers the volume of produce offered for sale.

Conclusion

This study contributes to the literature by applying the generalized two-part fractional regression model (GTP-FRM) to jointly examine both the participation decision and participation intensity among paddy farmers. By explicitly accounting for the bounded nature of the dependent variable and the interdependence between the two stages of market behavior, the model provides a more appropriate and robust framework for analyzing commercialization dynamics. The findings indicate that human capital, asset endowment, production capacity, and institutional factors jointly shape farmers' market outcomes. Education is negatively associated with paddy market participation; however, this does not imply withdrawal from markets. Rather, it reflects a strategic shift toward value addition, as more educated farmers tend to process paddy into rice to capture higher margins. Farm size exhibits heterogeneous effects: medium-scale farmers are more likely to participate, whereas large-scale farmers allocate a smaller share of the gross value of their paddy production to paddy sales.

Institutional and market factors display differentiated impacts. Access to market information increases the probability of participation but reduces participation intensity in paddy markets, suggesting that informed farmers strategically redirect output toward higher-value channels. Similarly, access to milling facilities encourages rice marketing rather than paddy sales, reinforcing the role of value addition in shaping market behavior.

Overall, the results reveal that participation intensity is driven not only by resource endowment but also by strategic marketing choices. From a policy perspective, reducing transaction costs while supporting value addition and productivity growth emerges as a central priority. Strengthening rural infrastructure, improving market information systems, expanding access to productivity-enhancing inputs, and facilitating financial and organizational support constitute four key policy pillars. These priorities are directly grounded in the empirical findings, particularly the heterogeneous effects of farm size, the dual impact of market information, and the role of surplus production in shaping participation intensity.

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Policy Recommendations

Increasing investment in rural infrastructure- The results highlight the importance of post-harvest infrastructure, particularly storage and milling services, in influencing marketing choices. Investment in rural storage facilities and modern milling infrastructure can reduce post-harvest losses and transaction costs while enabling value addition and improved market integration.

Strengthen market information systems- Access to market information was found to be positively associated with both participation probability and intensity. Enhancing real-time price dissemination and market transparency through digital platforms and extension networks can reduce information asymmetries and support more strategic marketing decisions among paddy producers.

Support formation and capacity-building of farmer groups- Given the significant role of marketing channels and location in shaping participation outcomes, strengthening farmer organizations can improve bargaining power, reduce intermediation costs, and facilitate access to more favorable market outlets. Cooperative structures may help farmers overcome spatial and transaction cost constraints identified in the analysis.

Expand access to agricultural credit and financial services- The empirical results indicate that factors such as surplus production and farm size are positively associated with both participation probability and participation intensity. Improving access to agricultural credit can enable smallholder farmers to invest in productivity-enhancing inputs and technologies, thereby increasing their marketable surplus and strengthening their engagement in the paddy market.

Tailor extension services to market orientation- Extension access was positively associated with participation outcomes. Expanding extension programs to include marketing literacy, value chain awareness, and price negotiation skills, alongside technical production advice, can further enhance farmers' commercialization capacity.

Future Research Directions

While this study provides valuable insights into the factors influencing market participation among paddy farmers in Golestan Province, several areas require further investigation. Comparative studies should be conducted in other paddy-producing provinces, such as Mazandaran and Gilan, to identify region-specific challenges and opportunities in the rice value chain. This will help develop a more comprehensive understanding of market participation dynamics across Iran.

The broader socio-economic impacts of market participation, including its effects on household welfare, food security, and rural development, remain underexplored. Future studies should assess these impacts to provide a comprehensive understanding of how market participation shapes farmers' livelihoods and contributes to sustainable agricultural development in Iran. In addition, subsequent research may explore potential interaction effects among structural, institutional, and production-related factors to examine whether certain determinants reinforce or moderate each other in shaping participation behavior. Expanding the analytical framework to incorporate financial intermediation, market risk, and organizational participation could further enrich the understanding of commercialization dynamics in the agricultural sector.

Methodological Improvements

The primary limitation of this study relates to the use of cross-sectional data, which constrains the ability to capture dynamic adjustments in farmers' market participation behavior and limits causal interpretation. Although the econometric framework corrects for observable heterogeneity and potential selection bias, unobserved time-varying factors cannot be fully addressed within a single-period dataset.

A second limitation concerns the identification strategy in the Heckman and GTP-FRM specifications. Access to mills and storage facilities has been used as exclusion restrictions. While these variables are theoretically justified and statistically valid within the model, alternative instruments could potentially strengthen identification robustness. In addition, certain environmental and infrastructural dimensions, such as climate variability, water availability, and transportation conditions, are not explicitly modeled, which may limit the comprehensiveness of the analysis.

A third methodological consideration relates to the sample size relative to the number of predictors. Although the LASSO procedure reduced the initial set of 21 candidate variables to 15 relevant predictors, the ratio of observations to estimated parameters in the two-part nonlinear framework remains modest. This may affect the precision of some estimates and the power of significance tests, especially for variables with small effect sizes. Nevertheless, the use of LASSO helped to preserve degrees of freedom and mitigate overfitting given the cross-sectional nature of the data.

Appendix

Appendix A: Disaggregated Hypotheses

H1: In Golestan Province, larger farm size is positively associated with the probability (H1a) and the extent (H1b) of participation in the paddy market.

H2: In Golestan Province, tractor ownership is positively associated with the probability (H2a) and the extent (H2b) of participation in the paddy market.

H3: In Golestan Province, greater paddy production surplus is positively associated with the probability (H3a) and the extent (H3b) of participation in the paddy market.

H4: In Golestan Province, access to storage facilities is negatively associated with the probability (H4a) and the extent (H4b) of participation in the paddy market.

H5: In Golestan Province, access to milling services is negatively associated with the probability (H5a) and the extent (H5b) of participation in the paddy market.

H6: In Golestan Province, access to extension services is positively associated with the probability (H6a) and the extent (H6b) of participation in the paddy market.

H7: In Golestan Province, access to market information is positively associated with the probability (H7a) and the extent (H7b) of participation in the paddy market.

H8: In Golestan Province, marketing channels are significantly associated with the probability (H8a) and the extent (H8b) of participation in the paddy market.

H9: In Golestan Province, farm location is significantly associated with the probability (H9a) and the extent (H9b) of participation in the paddy market.

H10: In Golestan Province, higher education level is negatively associated with the probability (H10a) and the extent (H10b) of participation in the paddy market.

H11: In Golestan Province, larger household size is negatively associated with the probability (H11a) and the extent (H11b) of participation in the paddy market.

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مقاله پژوهشی

جلد ۴۰، شماره ۲، تابستان ۱۴۰۵، ص. ۲۳۶-۲۱۱

عوامل تعیین‌کننده مشارکت در بازار شلتوک و شدت آن در ایران: شواهدی مبتنی بر مدل رگرسیون کسری دو بخشی تعمیم‌یافته

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تاریخ دریافت: ۱۴۰۴/۰۹/۱۳

تاریخ پذیرش: ۱۴۰۵/۰۲/۲۶

چکیده

برنج به‌عنوان دومین محصول راهبردی پس از گندم، نقشی محوری در پایداری معیشت روستاییان و تأمین درآمد کشاورزان ایران ایفا می‌کند. با وجود این جایگاه، موانع ساختاری، نهادی و مرتبط با بازار، همچنان تجاری‌سازی مؤثر را برای تولیدکنندگان شلتوک با محدودیت مواجه ساخته است. پژوهش حاضر با هدف شناسایی عوامل تعیین‌کننده تصمیم به مشارکت و شدت مشارکت در بازار شلتوک در استان گلستان انجام شد. داده‌ها در فصل زراعی ۱۴۰۳–۱۴۰۲ با استفاده از پرسشنامه‌ای ساختاریافته، از ۱۵۰ تولیدکننده شلتوک جمع‌آوری گردید. تحلیل داده‌ها با به کارگیری مدل رگرسیون کسری دو بخشی تعمیم یافته (GTP-FRM) صورت گرفت که به‌طور همزمان تصمیم دودویی مشارکت و سهم شلتوک عرضه شده به بازار را برآورد می‌کند و در عین حال ماهیت کران دار متغیر وابسته و وابستگی احتمالی بین مراحل مختلف مشارکت را نیز مدنظر قرار می‌دهد. متغیرهای توضیحی شامل ویژگی‌های سرمایه انسانی (تحصیلات و بعد خانوار)، دارایی‌های سرمایه‌ای (سطح زیر کشت و مکانیزاسیون) و متغیرهای نهادی و دسترسی به بازار (خدمات شالیکوبی، تأسیسات انبارداری، اطلاعات بازار و کانال‌های بازاریابی) بودند. یافته‌ها حاکی از آن است که ۶۴ ٪ از کشاورزان در بازار شلتوک مشارکت دارند و به‌طور میانگین ۴۹ ٪ از ارزش ناخالص تولید به فروش می‌رسد. تحصیلات رابطه منفی با مشارکت در بازار شلتوک دارد که بیانگر تغییر راهبردی به سوی ارزش افزایی است؛ به گونه‌ای که کشاورزان دارای سطح تحصیلات بالاتر، تمایل دارند محصول شلتوک خود را فرآوری و به‌صورت برنج به بازار عرضه نمایند. در مقابل، افزایش سطح زیر کشت و مازاد تولید، به‌طور معناداری احتمال مشارکت و شدت آن را افزایش می‌دهد. متغیرهای نهادی و بازار نیز نقش‌های متمایزی ایفا می‌کنند: دسترسی به اطلاعات بازار، احتمال مشارکت را افزایش می‌دهد، در حالی‌که دسترسی به تسهیلات شالیکوبی، احتمال مشارکت در بازار شلتوک را کاهش و می‌تواند باعث افزایش مشارکت در بازار برنج شود. به‌طور کلی، نتایج نشان می‌دهد که تجاری سازی در استان گلستان نه تنها تحت تأثیر ظرفیت تولید، بلکه تحت تأثیر راهبردهای ارزش افزایی و ملاحظات هزینه‌های مبادله در چارچوب سیاست‌ها و ساختارهای بازار موجود شکل می‌گیرد. از این رو، طراحی و اجرای سیاست‌هایی که بر بهبود زیرساختهای فرآوری روستایی، تقویت سامانه‌های اطلاعات بازار، افزایش مازاد تولید و کاهش موانع نهادی متمرکز باشند، می‌تواند به‌طور مؤثرتری از مشارکت و تجاری‌سازی پایدار در میان تولیدکنندگان شلتوک استان گلستان حمایت کند.

واژه‌های کلیدی: برنج، محدودیت‌های نهادی، مدل‌های کسری، مشارکت در بازار، هزینه‌های مبادله

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https://doi.org/10.22067/jead.2026.96839.1407

Contents

Agricultural Economics & Development

(AGRICULTURAL SCIENCES AND TECHNOLOGY)

Vol. 40 No.2 Summer 2026

Published by: Ferdowsi University of Mashhad (College of Agriculture) Iran.

Editor in charge: Valizadeh, R. (Ruminant Nutrition)

General Chief Editor: Shahnoushi, N(Economics & Agricultural)

Publisher: Ferdowsi University of Mashhad (College of Agriculture)

Address: College of Agriculture, Ferdowsi University of Mashhad, Iran

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Ferdowsi University of Mashhad

Journal of Agricultural Economics & Development

(Agricultural Sciences and Technology)

Vol.40 No.2

2026

ISSN:2008-4722

Contents