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

جلد ۳۸ شماره ۴
سال ۱۴۰۳

شماره پیاپی ۶۵
شاپا: ۴۷۲۲-۲۰۰۸

عنوان مقالات

نشریه اقتصاد و توسعه کشاورزی

(علوم وصنایع کشاورزی)

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

جلد 38 شماره4 زمستان 1403

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 _ دبیرخانه نشریات علمی _ نشریه اقتصاد و توسعه کشاورزی

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بسم الله الرحمن الرحیم

مندرجات

Journal of Agricultural Economics & Development

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

Research Article
Vol. 38, No. 4, Winter 2025, p. 351-370

A Data Mining Approach to Consumers' Choice of Retail Market: The Case of Urban Retail Markets in Iran

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Received: 20-05-2024
Revised: 06-07-2024
Accepted: 08-07-2024
Available Online: 08-07-2024

How to cite this article:
Hashemzadeh, H., Yousefian, N., Esfandiari Bahraseman, S., Karbasi, A., & Firoozzare, A. (2025). A data mining approach to consumers' choice of retail market: The case of urban retail markets in Iran. *Journal of Agricultural Economics & Development, 38*(4), 351-370. https://doi.org/10.22067/jead.2024.88151.1269

Abstract

Urban retail markets are state-owned retail markets that were recently established in Iran to increase the welfare of consumers and producers. To achieve this goal and expand its presence in the Iranian retail sector, it is essential to gain a comprehensive understanding of consumer behavior within these markets. This study examines the various socio-economic factors influencing consumers' decisions in the retail market by using the C4.5 algorithm. The data were collected using a random sampling method through a survey of 189 consumers, focusing on the population of Mashhad, Iran, during 2019-2020. Results revealed that awareness of available discounts significantly drives consumer choices in urban retail markets. Despite existing discounts, awareness among consumers remains low, suggesting a need to review promotional strategies within the marketing mix. The study also identifies previous purchases from urban markets, household income, and education as influential factors. Findings offer valuable insights for policymakers, market strategists, and stakeholders seeking to enhance the effectiveness of local retail markets in Iran. By leveraging insights into consumer behavior and market dynamics, these markets can thrive, benefiting Iran's retail sector and overall economy. Following the study, recommendations such as enhanced promotional campaigns, education-oriented strategies, loyalty programs, collaborations with local producers, and inclusive marketing policies was made aim to improve access for all consumers to urban retail markets.

Keywords: Consumer behavior, Data mining, Decision tree, Machine learning

https://doi.org/10.22067/jead.2024.85975.1237

Introduction

By identifying the critical factors that influence buyers' purchasing behaviors, marketers can craft strategies that align with these determinants, thereby securing their competitive edge in the market (Shamsher, 2016). Consumer behavior has remained a focal point in the discourse on retail marketing and decision-making for more than 70 years (Rahim *et al.*, 2021; Tian *et al.*, 2021).

Understanding consumer behavior involves delving into the psychological, social, and cultural factors that influence how individuals make purchasing decisions. Initially emerging as a specialized sub-discipline within marketing, the study of consumer behavior has consistently shown that purchasing decisions are influenced by a complex interplay of sociological and psychological factors (Applebaum, 1951; Dominici *et al.*, 2021; Donoghue *et al.*, 2021). Furthermore, contemporary research in this field views consumer behavior as an interdisciplinary social science, integrating insights from psychology, sociology, anthropology, ethnography, marketing, and economics, particularly behavioral economics (Razu & Roy, 2019).

In recent years, Iran's retail industry has undergone a dramatic transformation, marked by the growing prominence of organized retail. This shift has brought profound changes within the sector (Shamsher, 2016; Gauri *et al.*, 2021). These changes include the proliferation of shopping malls, supermarkets, and hypermarkets, which have altered traditional shopping patterns and consumer expectations. The rise of organized retail in Iran has been accompanied by an increase in consumer access to a wider variety of products and brands, more competitive pricing, and enhanced shopping experiences. This evolution has necessitated that retailers in Iran and similar markets pay closer attention to consumer behavior to remain competitive.

Iran's retail sector has evolved into an oligopoly, dominated by a few corporations operating chains of hypermarkets that supply most grocery products (Jofreh, 2013). Recently, state-operated urban retail markets have entered the Iranian market. State-owned retail markets were common in many countries, such as China, where urban consumers were limited to shopping at state-run establishments until 1978 (Veeck & Veeck, 2000). Although these markets are often criticized for inefficiencies (Hingley *et al.*, 2009), they must improve their performance to compete in a competitive environment.

The establishment of state-operated urban retail markets in Iran aims to ensure a direct and timely supply of fruits, vegetables, meat, poultry, fish, detergents, and sanitizers in the domestic market; support consumer rights; establish suitable and effective pricing; organize and regulate food markets; and facilitate the preparation and distribution of products by creating a direct connection between producers and consumers (Golriz Ziaie *et al.*, 2015). Considering these factors, promoting shopping in these markets enhances consumer welfare. Increasing the market share of urban markets can also lead to greater profits for producers, as these markets provide a platform for producers to sell their goods and reduce marketing margins (Thakur *et al.*, 2023). In this regard, marketers of urban retail markets must gain comprehensive knowledge about the factors that determine consumers' choice of retail market and how to influence their purchasing decisions (Liyanage *et al.*, 2020; Thakur *et al.*, 2023).

By understanding consumer preferences, behaviors, and the socio-economic variables that impact shopping habits, marketers can develop strategies that attract more customers to these markets. Several studies have looked for factors that influence consumers' choice of retail markets. For instance, Laine (2014) and Bhatti *et al.* (2015) identified that a store's product selection, previous experience, and location are crucial factors affecting consumers' retail market choices. Zulqarnain *et al.* (2015) examined factors influencing consumers' choice of retail stores, focusing particularly on

grocery stores. Pandey & Kaur (2018) conducted a study comparing retail marketing between rural and urban regions. Their findings underscored that urban as well as rural retail markets need to be addressed separately by any retail marketer because both regions offer several opportunities. Rasheed *et al*. (2018) found that if the store atmosphere is neat, the point of purchase display is attractive, promotional activities are influencing and payment facilities are provided then these will promote more impulse buying. Nguyen (2019) identified four factors influencing supermarket choice that includes location, perception of prices and products, employee attitudes, and references. Manuere (2023) investigated factors affecting customers' choice of supermarkets for grocery shopping in Chinhoyi town. The results of the study revealed that the location of the supermarket, children's play areas and parking areas are likely to influence the customers' choice of a supermarket.

The previous studies primarily focus on global contexts, overlooking specific insights crucial for the Iranian market. This gap hinders the development of customized strategies that align with local consumer preferences and socioeconomic dynamics. Moreover, the profound influence of culture on consumer behavior means that findings from other studies may not be applicable to Iran. This underscores the critical need for localized research to fill this gap and guide effective marketing strategies. The current study addresses these challenges by examining how socioeconomic variables impact consumer purchasing decisions in Iranian urban retail markets. Through the innovative application of machine learning algorithms for consumer classification, the study introduces a unique analytical framework tailored to predict and understand consumer behavior within Iranian urban retail markets. This approach aims not only to uncover the most influential socioeconomic factors shaping consumer choices but also to equip marketers with practical insights to enhance their ability to attract buyers to urban retail markets. In doing so, the study contributes to advancing our understanding of consumer behavior in a culturally specific context and introduces a novel method for consumer classification that can be adapted for similar studies.

Materials and Methods

Data Mining

Data mining is the investigation and examination of large amounts of data to find significant patterns and rules (Berry & Linoff, 2000). It tries to discover potentially useful, interesting, and previously unknown patterns from a large collection of data (Ram, 2022). Classification is one of the main goals associated with data mining. It is the characteristic knowledge that displays the shared properties of the same type of items and the shared characteristics of differences between different items (Vindigni *et al*., 2022). It aims to retrieve rules from the database. The most popular multidimensional classification technique is decision tree (Moitra *et al*., 2021; Quinlan, 2014), which is used in this survey.

Decision Tree

Decision trees (DT) are powerful tools that have been widely used to build classification models (Kotsiantis, 2013; Ooi *et al*., 2017). The algorithm created by a DT can be turned into multiple IF-THEN rules that display the relationship between output and input traits. A DT is made up of one root node, a few internal nodes, and numerous leaf nodes. The DT begins with the root node. The internal nodes join the leaf and root nodes. Each leaf node is equipped with a class label. The routes leading from the root node to the leaf nodes show the classification rules (Dev & Eden, 2019; Meng *et al*., 2020). The advantages of using DT compared with other methods are (Kotu & Deshpande, 2018; Nisbet *et al*., 2018):

- DT is more accurate compared with other data mining methods.
- It can be used for a wide range of data types, including continuous and discrete data.
- Compared with other classification methods, it requires less time.
- Extracted rules are simple to understand

and interpret.

Commonly utilized DT algorithms include the CART, Iterative Dichotomizer (ID3), and C4.5 algorithms (Barh, 2020). All the classification methods have a similar structure, to create a high-quality tree with a low error rate. Most of them use top-down greedy search to traverse the possible spaces of a DT. However, the majority of them have different branching and branch-cutting techniques (Han *et al.*, 2022). Developed by Quinlan (1996), C4.5 is an improved version of ID3 that uses the information gain ratio as the standard for selecting attributes rather than information gain. Like the CART algorithm, C4.5 considers each node as recursive and chooses the optimal part. This trend will continue until there are no optimal parts left. There are two main advantages associated with the C4.5 algorithm. First, it can handle continuous attributes better than the CART algorithm (not limited to binary attributes); second, the overfitting issue that exists with the ID3 technique can be resolved using the C4.5 approach (Zaki & Meira, 2020; Sun *et al.*, 2007). The process of forming a decision tree and selecting an attribute is described below (Sugumaran & Ramachandran, 2007; Kumar *et al.*, 2014):

1- A collection of available features is the input of the algorithm, and DT is the output of it.
2- Leaf nodes of the DT represent the class labels, and other nodes represent classified classes.
3- The tree's branches stand in for each predictive value of the feature node they originate from.
4- Starting at the tree's root and proceeding through it until one reaches a leaf node (which offers a categorization of the instance), the DT can be used to categorize feature vectors.
5- Using the right estimation criteria, one can choose the most beneficial feature for classification at each decision node in the DT. The ideas of entropy reduction and information gain—discussed in the following subsection—are applied in the criteria used to determine the optimal feature.

In the C4.5 algorithm, the decision tree is built from top to bottom. This technique uses information gain to determine which attribute should be utilized to categorize the current subset of data. Then, to choose the best alternative for the next node, the same process takes place for the data of each branch (Cherfi *et al.*, 2018). 'Information gain' is the anticipated loss of entropy owing to portioning the samples according to a specific attribute, while 'Entropy' describes the impurity of an arbitrary collection of examples. Increasing information lessens uncertainty. Entropies of the initial system and the system after information is added, are compared in information gain. Information gain (S, A) of a feature *A* relative to a collection of examples *S* is defined by the following formula (Reddy & Chittineni, 2021; Lintang *et al.*, 2022):

$$\text{Gain}(S,A) \equiv \text{Entropy}(S) - \sum v \in Value(A) \frac{|Sv|}{S} \text{Entropy}\ (S_v \quad (1)$$

Where *Values (A)* refers to the collection of all potential values for *A* attribute, and corresponding S_v designates the subset of *S* for which feature *A* has value *v*. *S* stands for the original collection's entropy in the equation above, and *A* is the expected value of entropy. The entropies belonging to each subset Sv are added together to get the expected entropy denoted by the word *A*. *Gain (S,A)* is the expected depletion in entropy as a result of the known value of attribute *A*. Entropy is:

$$Entropy(S) = \sum_{i=1}^{c} - p_i \log_2 p_i \quad (2)$$

Where P_i is the proportion of S belonging to class 'i' (Kumar *et al.*, 2014). The present study used the J48 algorithm (equal to the C4.5 algorithm in WEKA software) for learning the decision tree.

Goodness-of-fit of decision-tree models

The performance of the decision tree can be measured by indexes below:

- True Positive Rate
- False Positive Rate
- Precision
- Recall

- F amount

The True Positive Rate (TPR) criterion, also called the Hit Rate, is the ratio of buyers who are correctly classified in each group and is calculated as follows:

$$\text{TP Rate} \approx \frac{\text{Number of consumers correctly classified}}{\text{Total number of consumers}} \quad (3)$$

False Positive Rate represents the ratio of buyers who are classified incorrectly by DT and is calculated as follows:

$$\text{FP Rate} \approx \frac{\text{Number of consumers incorrectly classified}}{\text{Total number of consumers}} \quad (4)$$

The measures of Precision and Recall are also calculated with the following formulas:

$$\text{Precision} = \frac{\text{TP rate}}{\text{TP rate}+\text{FP rate}} \qquad \text{Recall} = \text{TP rate} \quad (5)$$

The index that combines FPR and TPR is the harmonic mean of Precision and Recall and is calculated as below (Walkinshaw, 2013):

$$F - Measure = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (6)$$

Cohen's kappa (κ) statistic is a chance-corrected method for measuring agreement (rather than association) among raters. It answers the question of: What percentage of values not expected to be in agreement (by chance) are in agreement? The formula of Kappa is:

$$\widehat{K} = \frac{f_0 - f_E}{N - f_E} \quad (7)$$

Where f_0 is the relative observed agreement among raters, f_E is the hypothetical probability of chance agreement, and N is the total number of observations (Cohen, 1960). The Kappa result can be interpreted as follows: values ≤ 0 denote no agreement, 0.01-0.20 indicate no to slight agreement, 0.21-0.40 indicate fair agreement, 0.41- 0.60 indicate the moderate agreement, 0.61-0.80 indicate substantial agreement and 0.81-1.00 denote almost perfect agreement (McHugh, 2012).

Data

Examining urban retail markets in Mashhad is particularly significant due to the city's dual role as a major hub for both domestic residents and international tourists. With millions of visitors annually, Mashhad's retail sector experiences unique dynamics influenced by diverse consumer behaviors shaped by cultural, social, and economic factors specific to the region. In this context, a questionnaire was designed to identify and understand the socio-economic factors that impact consumers' choices in retail markets. Initially, pertinent literature was reviewed to select the most relevant socio-economic variables affecting consumer behavior. Following this, the questionnaire was refined through focus group discussions to comprehensively capture the nuances of these factors in Mashhad's retail markets. By conducting a pre-study, the sample size was determined, and necessary tests to ensure its validity and reliability were performed. In this regard, 30 questionnaires were filled out. It should be noted that the data were collected in 2019-۲۰۲۰ . The results of this sample showed that the variance of the studied attribute, which was calculated based on the probability of each of the dependent variable groups, is equal to 0.238. The current study employed a simple random sampling method to ensure equal opportunity for every individual in the studied population to be selected and to prevent bias in sample selection. Furthermore, the sample size of 189 observations was determined based on Equation 10.

$$n = \frac{Z^2\delta_i^2}{d^2} \quad (8)$$

When Z is the amount of normal variable with $1-\alpha$ confidence level (in the present study 95% confidence level is considered), d is the margin of error and δ_i^2 stands for the variance of the studied attribute. Prior to conducting the survey, the Ferdowsi University of Mashhad granted ethics approval. All the participants in the survey were informed regarding the aim of this study and were asked to answer in an honest manner. They were assured regarding the confidentiality of their response, the survey's scientific intent, and their privacy. All the participants were responsible for the shopping in their families and were older than 18 years old.

Result and Discussion

Descriptive statistics

To discover effective parameters and factors affecting the selection of urban retail markets by consumers, this study used the C4.5 algorithm. Table 1 shows the variables used in this study.

Table 1- Description of variables in the study

Variables	Explanation
Priority in purchase (decision variable)	purchase from other shops=1; purchase from urban market=2
Gender	Female=0; Male=1
Age	Less than 40=1; More than 40=2
Job	Housekeeper, Unemployed, Retired=1; Self-employed=2; Employment in public and private sector jobs=3
Education	Less than university education =1; University education=2
Distance from urban market	Near=1; Far=2
Previous purchase from urban Markets	No=0; Yes=1
Existence of discounts and awareness of that in the urban markets	No=0; Yes=1
Household income per month	Less than 357 dollars =1; Between 357 and 655 dollars = 2; More than 655 dollars = 3

According to Table 1, effective socio-economic variables in the selection of urban retail markets include gender, age, job, education, distance from the urban markets, previous purchases from the urban markets, awareness of the discounts in the urban markets, and household income.

Fig. 1 provides an overall illustration of the sample. It is made up of nine different figures, each of which belongs to a different variable. On the left side of each picture are those who coded with the least number (0 or 1), and on the right side are those with higher codes. Those with blue colors have prioritized purchasing from other markets over urban markets.

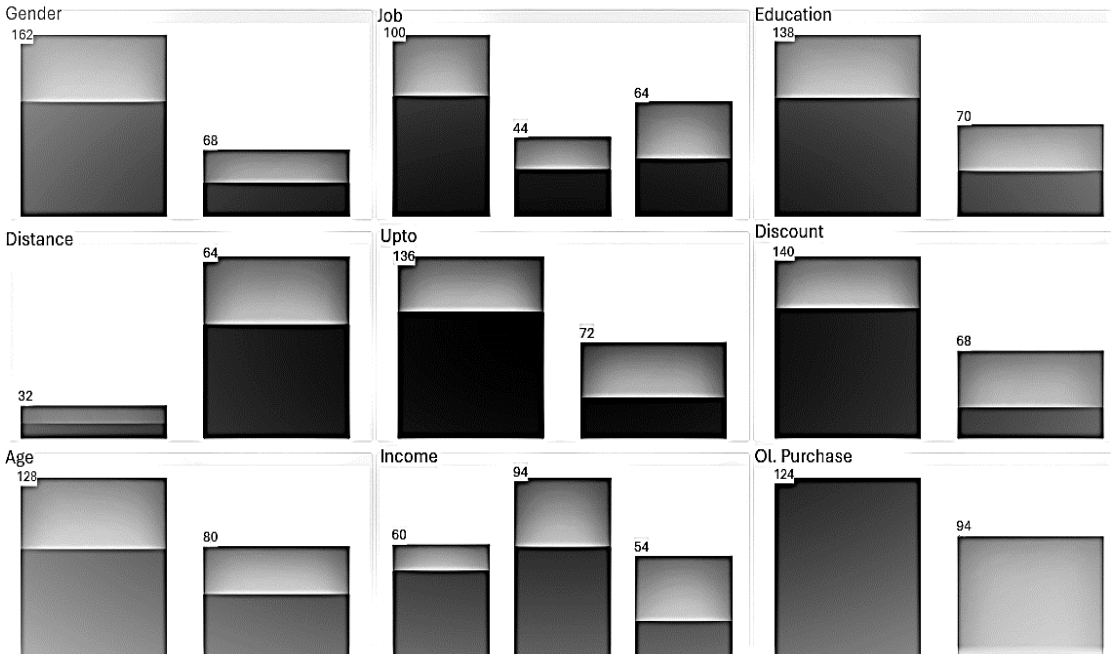

Figure 1- The relation between the independent variables and the purchasing from the urban markets or other shop

Table 2- Descriptive analysis of variables

Variable	Decision group variable	Group	Percentage
Gender	1	0	77.4
		1	22.6
	2	0	66.7
		1	33.3
	Total	0	73.1
		1	26.9
Age	1	1	62.9
		2	37.1
	2	1	59.5
		2	40.5
	Total	1	61.5
		2	38.5
Job	1	1	53.2
		2	21.0
		3	25.8
	2	1	40.5
		2	21.4
		3	38.1
	Total	1	48.1
		2	21.2
		3	30.8
Education	1	1	72.6
		2	27.4
	2	1	57.1
		2	42.9
	Total	1	66.3
		2	33.7
Distance from urban markets	1	1	11.3
		2	88.7
	2	1	21.4
		2	78.6
	Total	1	15.4
		2	84.6
Previous purchases from urban markets	1	0	75.8
		1	24.2
	2	0	50.0
		1	50.0
	Total	0	65.4
		1	34.6
Discount and being aware of it	1	0	80.6
		1	19.4
	2	0	47.6
		1	52.4
	Total	0	67.3
		1	32.7
Household Income Per Month	1	1	37.1
	2	2	46.8
	3	3	16.1
	1	1	16.7
	2	2	42.9
	3	3	40.5
	Total	1	28.8
		2	45.2
		3	26.0

Fig. 1 and Table 2 provide a detailed demographic overview of the sample. The study shows a predominant representation of female participants, particularly among shoppers from other markets compared to those from urban markets. Previous research in Iran has consistently observed a higher participation rate among women, a trend that is accentuated in this study. Awareness of discounts offered at urban markets is notably low, with a significant disparity between those who prioritize shopping elsewhere and others. A substantial portion of respondents had never made purchases from urban markets, indicating a potential barrier to market engagement. Interestingly, a large majority of participants perceive urban markets as distant from their residences, reflecting a common sentiment regardless of shopping preferences.

The results of the C4.5 algorithm

Using the C4.5 algorithm, the general behavior of consumers in their market selection is first investigated, and then the behavior of each consumer group is examined. Before analyzing the decision tree's algorithm in Fig. 1, it is required to investigate classification accuracy using various goodness of fit tests. Table 3 shows that the fitted tree in Table 1 has satisfactory classification accuracy, properly classifying more than 87 percent of first-group buyers, 83 percent of second-group buyers, and 86 percent of all purchasers.

Table 3- The general classification of consumers based on purchase priority from different markets using the C4.5 algorithm

Consumers	Number of observations	Results of decision tree C4.5 algorithm classification			
		Priority: purchase from other shops	Priority: purchase from the urban markets		
Priority: purchase from other shops (Group 1)	124	108 87.10%	16 12.91%		
Priority: purchase from the urban markets of the city (Group 2)	84	14 16.67%	70 83.33%		
Percentage of total correct classified observation		85.58			
Kappa Statistic		0.702			
Accuracy statistics based on class	TP rate	FP rate	Precision	Recall	Balanced F-score
Group 1	0.871	0.167	0.885	0.871	0.878
Group 2	0.833	0.129	0.814	0.833	0.824
Total	0.856	0.151	0.856	0.856	0.856

As shown in Fig. 1, the most effective socio-economic variable on buyers' choices is their awareness of the discounts in the urban markets, and after that, gender and household income are in the following order. The next degrees of significance are given to the factors of distance from the market, previous purchases from urban markets, and age.

In the DT with the C4.5 algorithm, the first number of each leaf node[1] represents consumer priority in choosing the market. It takes 1 if the consumers prefer buying from other markets, and it takes 2 if they prefer buying from the urban markets. The first number in parentheses in each leaf node represents how much data exists in the represented sample, and the second number illustrates the number of errors in the classification of buyers.

According to the classification that has been done based on the C4.5 algorithm of the DT, around 40% of buyers are women who were not aware of the urban markets' price discounts,

1- Each decision tree has two kinds of nodes: internal nodes and leaf nodes. Each internal node or non-leaf node is illustrated by an attribute in a way that represents a "test" on an attribute, and there are branches equal to the number of possible answers, and each of them shows the outcome of a test. Each leaf node also represents a class or group of answers.

were far from the urban markets, and had never purchased from these markets. These buyers will purchase from shops near their place of residence.

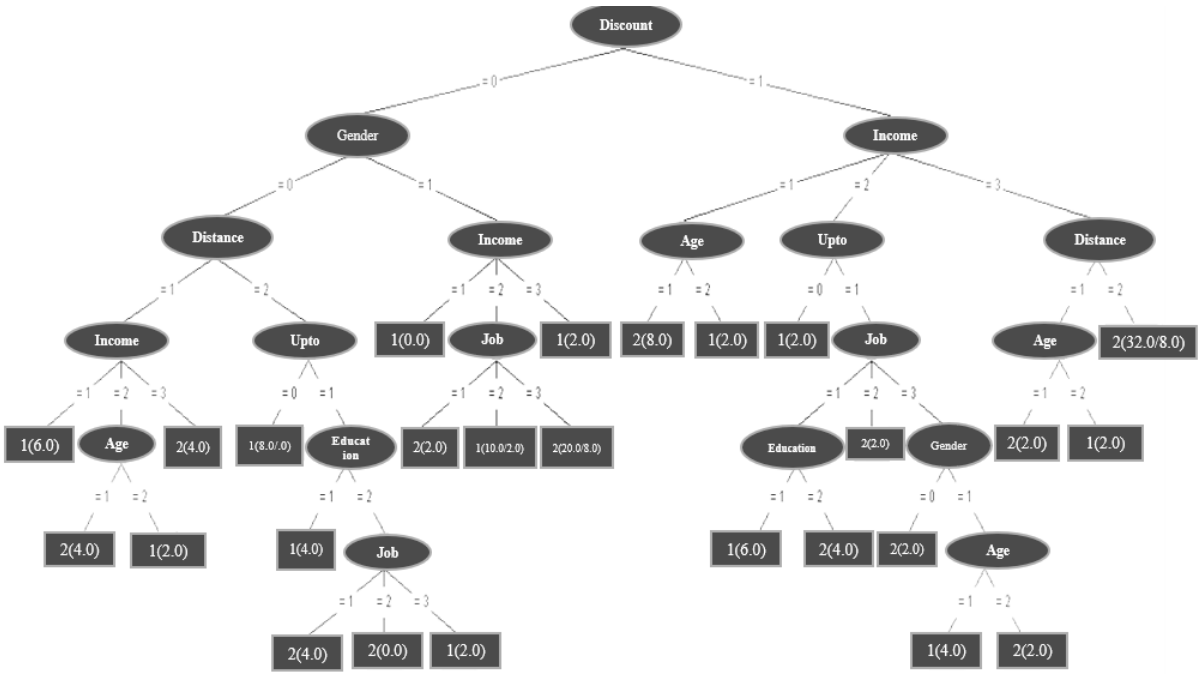

Figure 2- C4.5 algorithm of buyers' general behavior in choosing among different markets

According to Fig. 2, another group that makes up a high proportion of buyers is middle-income men who are unaware of discounts in the urban markets. In this group, those who work as employees choose the urban markets, while those with self-employed jobs choose other shops. Buyers who have an average income level and are aware of the discount in the urban markets do not buy from these markets if they do not have experience buying from them. However if they do have the experience, purchasing or not purchasing from the urban markets depends on other variables, such as job, gender, education, and age, which are explained in Fig. 1. Greenacre & Akbar (2019); Daoudi & Develi (2022) also stated that age and income play a significant role in influencing consumer buying behavior. The noteworthy point about this tree is how the middle-income group, as opposed to the low-income and high-income groups, follows a more complicated algorithm from all the branches that lead to household income. Planners and policymakers of urban marketplaces should consider this since this group makes up the majority of the population. Therefore, it is crucial to take additional factors such as age, gender, occupation, and education into account for the middle-income group. Investigating this tree also illustrates that people with a higher level of awareness regarding discounts are more likely to purchase from these markets. For a better understanding of consumer behavior, this behavior is discussed in different groups based on gender, education, and distance. Fig. 3 and 4 represent male and female consumers' behavior, respectively, and Table 4 represents the information accuracy of the DT represented in that figure. As shown in Table 4, the DT could accurately classify female consumers' purchasing patterns in 87 percent of cases, while male consumers' purchasing patterns were correctly classified in 86 percent of cases. Kol & Levy (2023); Chen *et al.* (2022); Savaşkan & Çatı (2021) stated that female customers are more interested in discounted products and gender difference affects the purchasing pattern. Furthermore,

Table 4- Consumer classification based on gender and purchase priority using the C4.5 algorithm

Consumers	Number of observations		Results of decision tree C4.5 algorithm classification			
			Priority: purchasing from other markets		Priority: purchasing from urban markets of city	
	Female	Male	Female	Male	Female	Male
Priority: purchasing from other shops (Group 1)	96	28	88	24	8	4
			91.67%	85.71%	8.33%	14.28%
Priority: purchasing from urban markets of city (Group 2)	56	28	12	4	44	24
			21.42%	14.28%	78.57%	85.71%
			Female		Male	
Percentage of total correct classified observation			86.84%		85.71%	
Kappa Statistic			0.715		0.714	

Accuracy statistic based on class	TP rate		FP rate		Precision		Recall		Balanced F-score	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Group 1	0.917	0.857	0.214	0.143	0.880	0.857	0.917	0.857	0.898	0.857
Group 2	0.786	0.857	0.083	0.143	0.846	0.857	0.786	0.857	0.815	0.857
Total	0.868	0.857	0.166	0.143	0.868	0.857	0.868	0.857	0.867	0.857

The DT from the analysis of female consumer behavior is shown in Fig. 3. It demonstrates that for this group of consumers, awareness of the discounts is the most significant factor, and then the variables of distance from the urban markets and education are on the second level of effectiveness. The third most effective variable in influencing consumers' choices is income and previous purchases from the urban markets. In the case of the behavior analysis of male consumers, Fig. 4 illustrates that the job is the most significant variable, followed by income and previous purchases from the urban markets. Age, distance from the urban markets, and discount awareness are on the third level of effectiveness. Gomes (2018) emphasizes that education level, gender, and occupation profoundly impact individuals' shopping behavior patterns, playing pivotal roles in shaping consumer preferences, decision-making processes, and shopping habits across diverse demographic groups. Furthermore, Taylor *et al.* (2019) and Chandrakala *et al.* (2023) highlighted that discounts are a significant factor influencing consumer purchasing behavior. Šostar & Ristanović (2023) highlight that age, gender, and employment status are influential factors in shaping consumer behavior.

According to Fig. 3, if women are aware of the discount offered by the urban markets and have a high level of education, they purchase from the urban markets, but if they have a low level of education and a medium level of income, they will purchase from an alternative market. If planners want to draw in more consumers, they should take into account the significant impact of discount awareness on women's purchasing habits. Female consumers will not purchase from urban markets if they do not know about the discount, the distance between their place of residence and these markets is far, and they have not previously purchased from these markets. Planners must adopt and carry out remedial policies to address this problem.

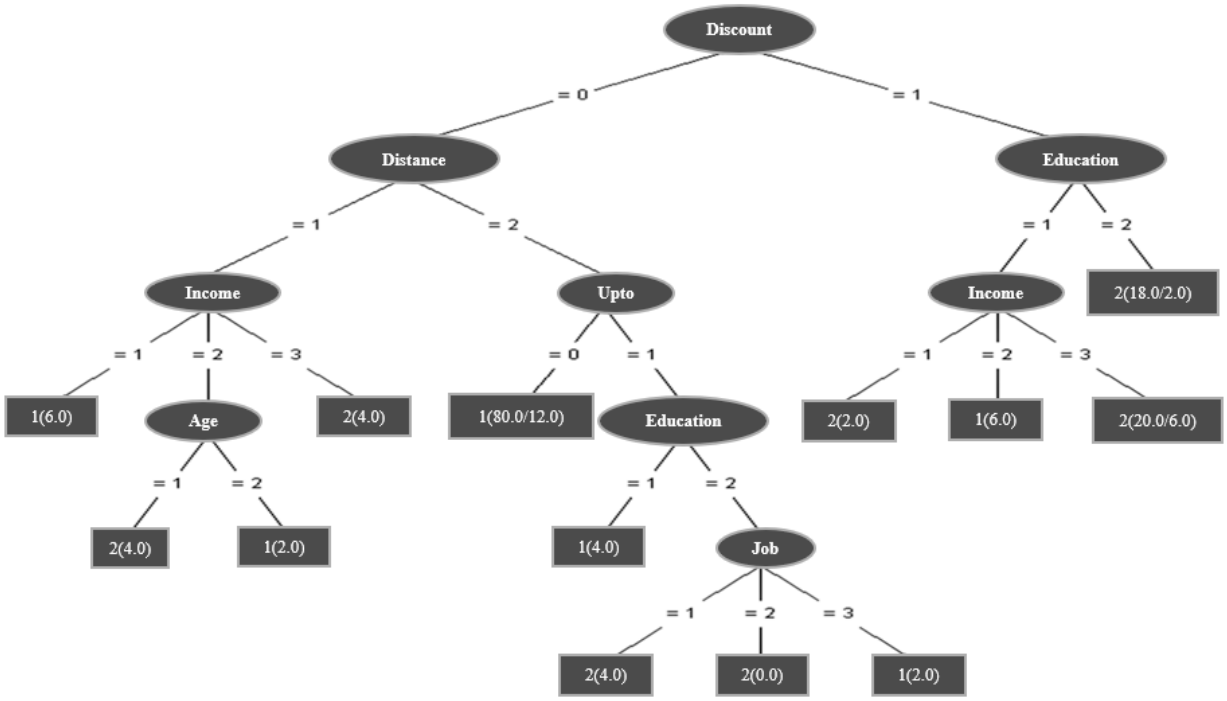

Figure 3- C4.5 algorithm of female buyers' buying behavior in choosing between different alternatives of market

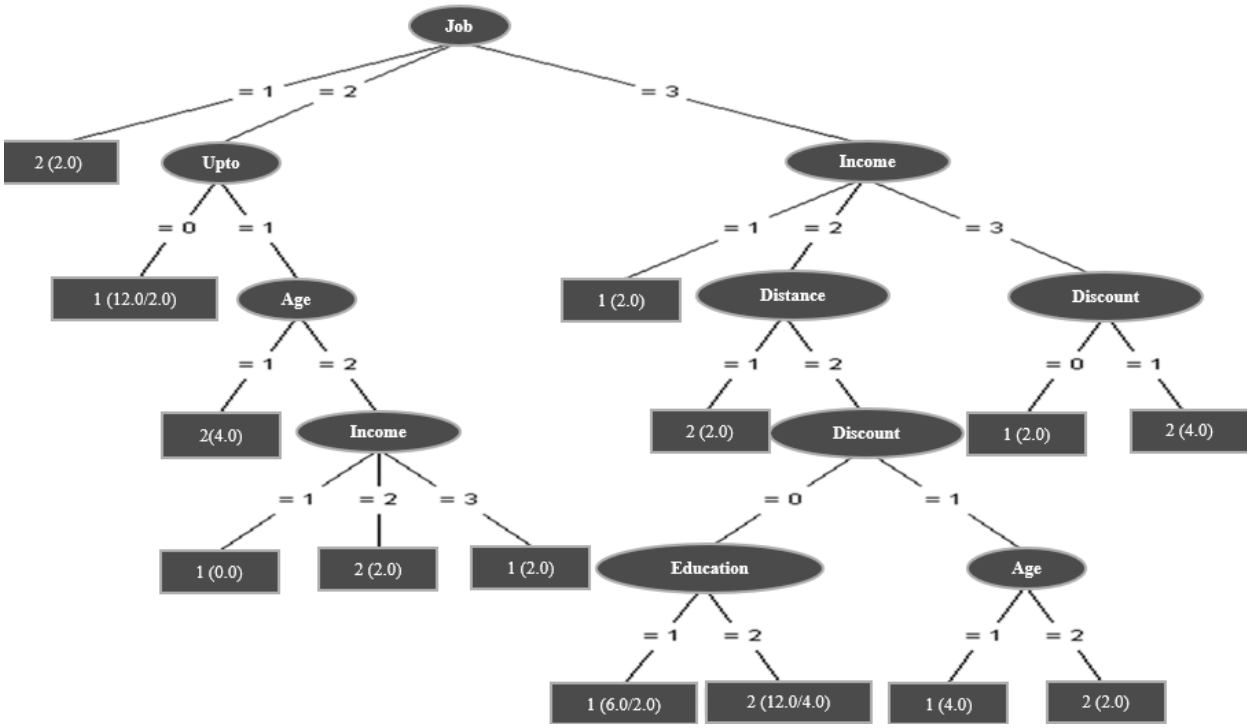

Figure 4- C4.5 algorithm of male buyers' buying behavior in choosing between different market alternatives

Regarding male consumers, Fig. 4 illustrates that those who are self-employed and have not previously shopped at urban markets tend to prefer other shops. However, employed men purchase from urban markets in two scenarios: first, if they have a high income and are aware of market discounts; and second, if they have a moderate income and reside near urban markets. Interestingly, they also shop at urban markets when they live far away, possess a high

level of education, and are unaware of market discounts. In line with these findings, Roy *et al.* (2021) suggested that local retailers' spot discounts could enhance market potential and influence consumer preferences toward purchasing. Table 5 discusses the behavior of consumers with and without university degrees. It indicates that the C4.5 algorithm of the DT could effectively classify consumers based on socioeconomic factors and simulate consumer behavior in two groups, including those with and without a university degree, to a great extent. Fig. 5 and 6 display the classification's outcomes.

Table 5- Consumer classification based on education and purchase priority using the C4.5 algorithm

Consumers	Number of observations		Results of decision tree C4.5 algorithm classification			
			priority: purchase from other shops		priority: purchase from urban markets	
	High[1]	Low	High	Low	High	Low
priority: purchase from other shops (Group 1)	32	90	26	86	6	4
			81.25%	95.56%	18.75%	4.44%
priority: purchase from urban markets (Group 2)	36	48	4	12	32	36
			11.11%	25.00%	88.89%	75.00%
			High		Low	
Percentage of total correct classified observation			85.71%		88.41%	
Kappa Statistic			0.714		0.734	

Accuracy statistics based on class	TP rate		FP rate		Precision		Recall		Balanced F-score	
	High	Low	High	Low	High	Low	High	Low	High	Low
Group 1	0.824	0.956	0.111	0.250	0.875	0.878	0.824	0.956	0.848	0.915
Group 2	0.889	0.750	0.176	0.044	0.842	0.900	0.889	0.750	0.865	0.818
Total	0.857	0.884	0.145	0.179	0.858	0.885	0.857	0.884	0.857	0.881

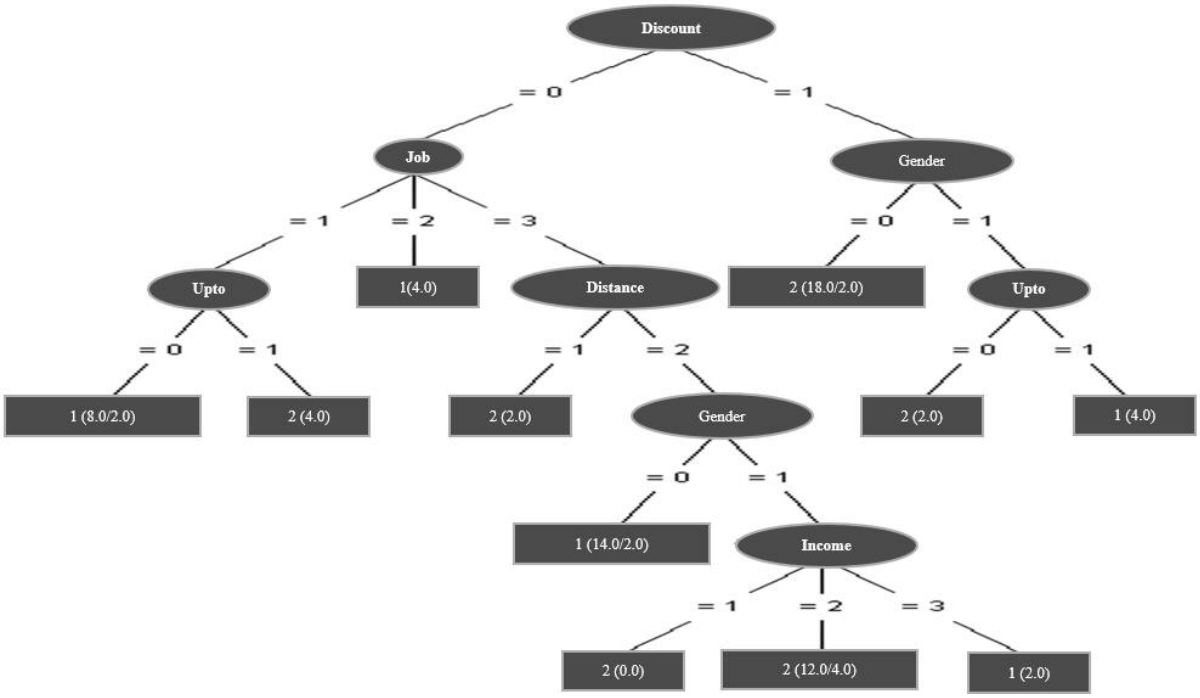

Figure 5- C4.5 algorithm of buyers' behavior in choosing different alternatives of the market who do not have a university degree

1- High means people with university degree and low means people with low degree

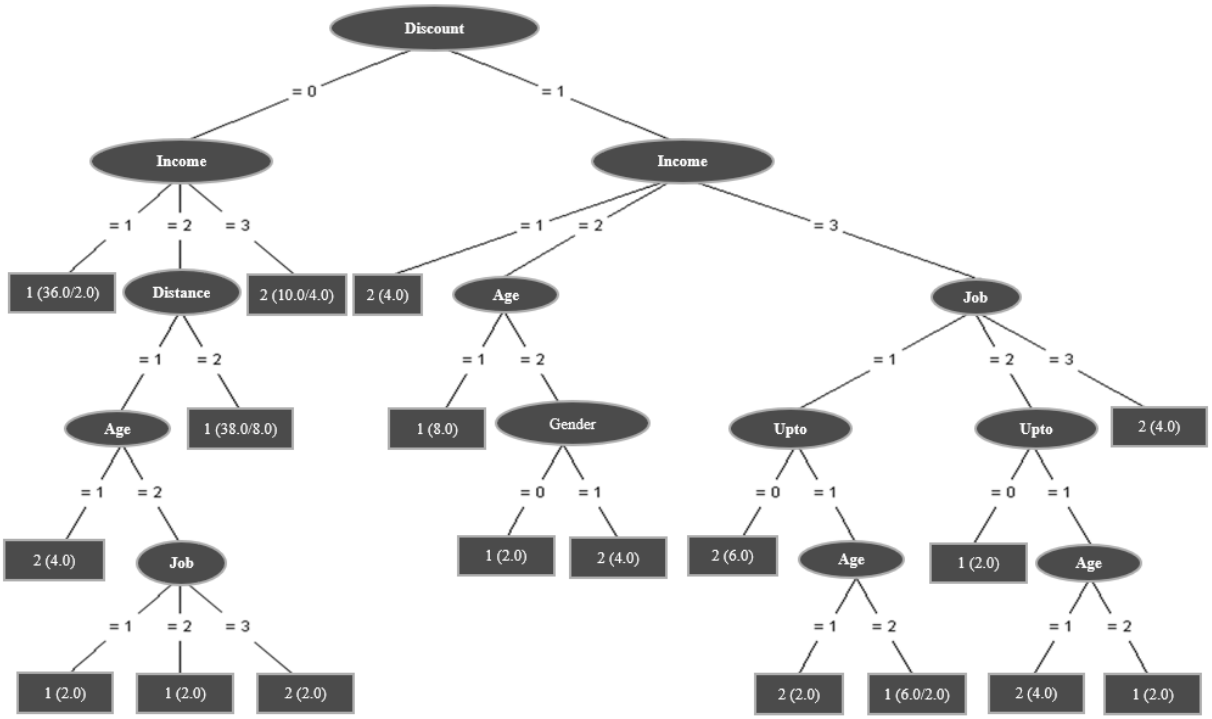

Figure 6- C4.5 algorithm of buyers' behavior in choosing different alternatives of the market who have a university degree

As it is shown in Fig. 5 and 6, the awareness of the urban market's discount is the most important component that influences consumers' choice among market options in both groups with and without a university degree.

In the group of consumers without university degrees, the second most essential criterion for both consumers with and without awareness of urban markets' discounts is their income. They are less likely to purchase from the urban markets if they are unaware of discounts and have low incomes. This is also true for consumers with a medium level of income who live far from the urban markets. Finally, since the distance from the urban markets is one of the important factors influencing consumer behavior, planners in this area can affect consumers' choices by selecting the right site.

Fig. 7, illustrates socio-economic variables that are effective on the behavior of consumers at a far and close distance from the urban markets. Prior to that, Table 6 provides information regarding different statistics that must be used to assess the accuracy of fitted trees. The DT correctly classified 82% of the consumers. Accuracy statistics based on class also illustrate the appropriate accuracy of the represented DT. Zulqarnain *et al.* (2015) also identified distance as a critical factor influencing consumers' choice of retail stores for grocery shopping. Terano *et al.* (2015), Yildirim *et al.* (2015) stated that significant differences in customer preferences based on age, gender, and education level.

As shown in Fig. 7 and 8, the consumer's decision to shop at the urban markets first depends on the discount offered at these markets and the consumers' awareness of that. One of the most crucial paths that planners should take into account is the path of women who are not aware of urban markets' discounts, live far away from the urban markets, and have never made purchases there before. These characteristics have prevented these individuals from choosing the urban markets over other markets. However, males living a far distance from the urban markets with a medium level of income who are not aware of discounts will buy from the urban markets if they have university degrees; otherwise, they will purchase from other shops. Therefore, the implementation of a specific marketing strategy for these groups can

lead to an increase in their purchases from these markets.

Table 6-Consumer classification based on distance from the urban markets and purchase priority using C4.5 algorithm

Consumers	Number of observations		Results of decision tree C4.5 algorithm classification			
			Priority: purchase from other shops		Priority: purchase from urban markets	
	Close	Far	Close	Far	Close	Far
Priority: purchase from other markets (Group 1)	14	110	12	98	2	12
			85.71%	89.09%	14.28%	10.90%
Priority: purchase from urban markets (Group 2)	18	66	4	18	14	48
			22.23%	27.27%	77.77%	72.73%
			Close		Far	
Percentage of total correct classified observation			81.25%		82.95%	
Kappa Statistic			0.625		0.630	

Accuracy statistic based on class	TP rate		FP rate		Precision		Recall		Balanced F-score	
	Close	Far	Close	Far	Close	Far	Close	Far	Close	Far
Group 1	0.857	0.891	0.222	0.273	0.750	0.845	0.857	0.891	0.800	0.867
Group 2	0.778	0.727	0.143	0.109	0.875	0.800	0.778	0.727	0.824	0.762
Total	0.813	0.830	0.178	0.211	0.820	0.828	0.813	0.830	0.813	0.828

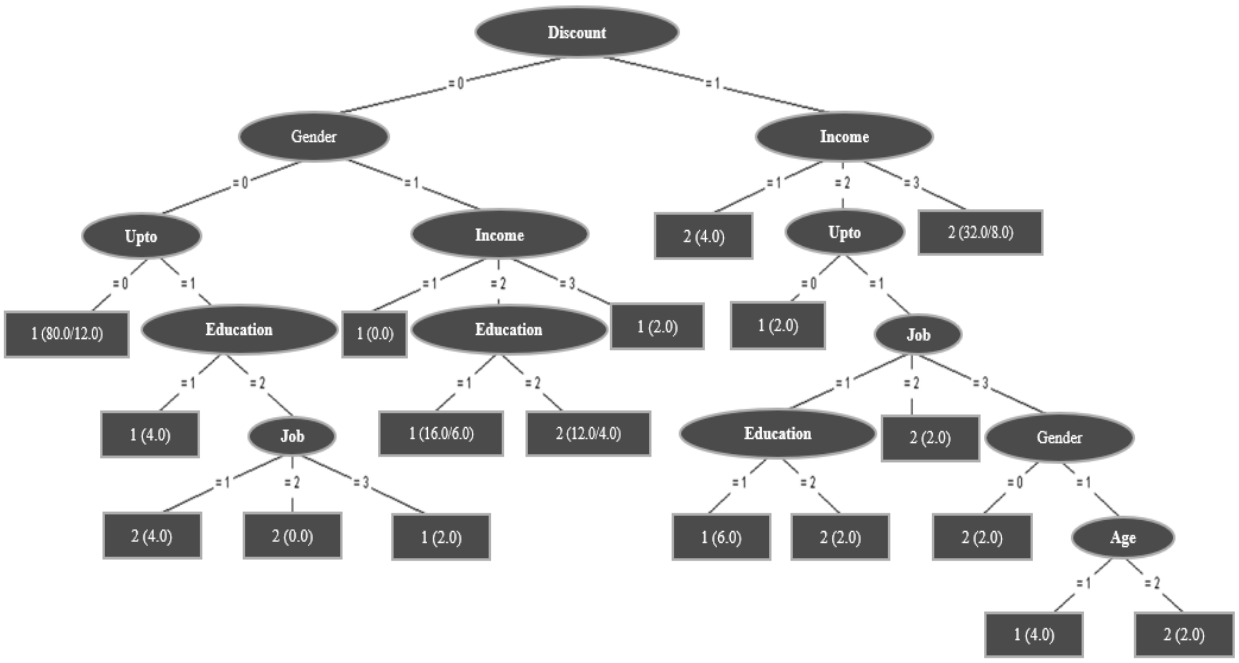

Figure 7- C4.5 algorithm of buyers' behavior with far distance from urban markets

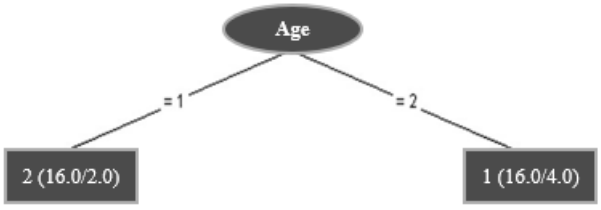

Figure 8- C4.5 algorithm of buyers' behavior at close distance from urban markets

Another considerable point about the distance from the urban markets is the fact that for those with a close distance from the urban markets, their choice between the urban markets and other shops only depends on age. Those who are less than 40 years old prefer urban markets, while others do not. Makgosa & Sangodoyin (2017) highlighted age as a critical determinant of consumers' store preferences. They categorized younger shoppers as recreational quality seekers and older shoppers as novelty–quality seekers.

Conclusion and Recommendation

This study used the C4.5 algorithm, one of the most accurate decision tree algorithms, to survey consumers and model their decision processes. In accordance with previous studies, this study demonstrates that C4.5 is a helpful tool for creating a hierarchical decision support model. It provides a simple schematic diagram of the consumers' decision-making process. This approach allows for the statistical testing of model validation. This enables the model's reliability to be taken into account. This study's decision tree has acceptable reliability. The findings highlight that consumer behavior is predominantly influenced by awareness of discounts, aligning closely with Alsini *et al*.'s (2023) findings on the impact of promotional campaigns on grocery shopping in Saudi Arabia. Discounts play a significant role in retail dynamics by boosting sales and enhancing customer satisfaction but also present challenges such as reduced profit margins and increased price sensitivity. Less than a third of consumers are aware of available discounts, suggesting deficiencies in current marketing strategies and the need for reassessment. Hecht *et al*. (2020) emphasized the importance of regularly reviewing marketing tactics to inform consumers about discounts effectively. In addition, Noor (2020) emphasized the significant impact of discounts on consumer buying behavior. Büyükdağ *et al.* (2020) also investigated the varying effects of discounts on men and women, highlighting that gender differences can influence how consumers respond to promotional offers.

The study also revealed that the majority of consumers in these markets have advanced degrees, likely due to policies targeting educated individuals or a lack of advertising that has inadvertently attracted this demographic. Conversely, those with lower education levels are less inclined to shop at these markets, likely due to factors such as income disparity, limited exposure to marketing, and less familiarity with urban retail markets. Hanaysha (2018) confirms that income is a key factor influencing purchase decisions. Kumar (2018) emphasized that comprehensive product offerings, convenience, and parking facilities contribute to the preference for urban retail markets. Current policies favoring high-income consumers highlight the need for equitable policy reviews to broaden market accessibility. Customer retention strategies, such as periodic discounts or conditional sales, can significantly influence subsequent consumer behavior and retention. In conclusion, this study provides valuable insights into consumer behavior within urban retail markets but acknowledges its limitations. Future research should explore comprehensive datasets, additional socio-demographic variables, and the long-term impact of marketing interventions. Based on these findings, the following suggestions are presented for policy-making and implementation:

1. Enhanced Promotional Campaigns: Enhanced promotional campaigns can effectively utilize social media and online advertising to raise awareness about ongoing discounts and special offers.
2. Education-oriented strategies: Collaborate with community centers and educational institutions to host workshops informing consumers about the benefits of urban retail markets. Furthermore, simplify access to discount details and product offerings through user-friendly apps or strategically placed informative brochures across the city.
3. Loyalty Programs: Introduce a loyalty

program that offers points or discounts to repeat customers, along with exclusive promotions, to attract more consumers to enroll and actively engage in the market.

4. Collaborations with Local Producers: Strengthen partnerships with local producers to ensure a consistent supply of high-quality products. Highlight these partnerships in marketing campaigns to emphasize the support for local businesses and fresh, local produce.
5. Inclusive Marketing Policies: Implement pricing strategies that cater to diverse income levels. Consider introducing tiered pricing or discount days tailored for low-income families to enhance affordability. Additionally, collaborate with community leaders and organizations to gain insights into the preferences of lower-income and less-educated consumers. Use this feedback to inform and adjust marketing and operational strategies accordingly.

By adopting these strategies, urban retail markets in Mashhad can enhance their appeal, attract a more diverse consumer base, and ensure sustainable growth. These efforts will not only boost consumer welfare but also support local producers and contribute to the overall economic development of the city.

References

1. Alsini, N., Kutbi, H.A., Hakim, N., Mosli, R., Eid, N., & Mulla, Z. (2023). Factors influencing grocery shopping choices and the prevalence of food label use among Saudi mothers: a cross-sectional pilot study. *Nutrition & Food Science*, *53*(2), 432-444. https://doi.org/10.1108/NFS-11-2021-0345
2. Applebaum, W. (1951). Studying customer behavior in retail stores. *Journal Market*, 172–178. https://doi.org/10.1177/002224295101600204
3. Barh, D. (2020). *Artificial Intelligence in Precision Health: From Concept to Applications*. Academic Press. https://doi.org/10.1016/B978-0-12-817133-2.09988-2
4. Berry, M.A., & Linoff, G.S. (2000). Mastering data mining: The art and science of customer relationship management. *Industrial Management & Data Systems*. https://doi.org/10.1108/imds.2000.100.5.245.2
5. Bhatti, K.L., Latif, S., & Latif, R. (2015). Factors affecting consumer's store choice behavior. *International Journal of Application or Innovation in Engineering & Management (IJAIEM)*, *4*(9), 71-77.
6. Büyükdağ, N., Soysal, A.N., & Kitapci, O. (2020). The effect of specific discount pattern in terms of price promotions on perceived price attractiveness and purchase intention: An experimental research. *Journal of Retailing and Consumer Services*, *55*, 102112. https://doi.org/10.1016/j.jretconser.2020.102112
7. Chandrakala, V.G., Sowmya, C.U., & Nagesha, H.G. (2023). A study on factors influencing the consumer buying behavior with reference to organized apparel retail outlets. *Journal of Innovations in Business and Industry*, *1*(2), 85-92. https://doi.org/10.61552/JIBI.2023.02.005
8. Chen, T., Samaranayake, P., Cen, X., Qi, M., & Lan, Y. (2022). The impact of online reviews on consumers' purchasing decisions: Evidence from an Eye-Tracking study. *Frontiers in Psychology*, *13*, 865702. https://doi.org/10.3389/fpsyg.2022.865702
9. Cherfi, A., Nouira, K., & Ferchichi, A. (2018). Very fast C4.5 decision tree algorithm. *Applied Artificial Intelligence*, *32*(2), 119-137. https://doi.org/10.1080/08839514.2018.1447479
10. Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, *20*(1), 37-46. https://doi.org/10.1177/001316446002000104
11. Daoudi, H., & İldem Develi, E. (2023). Impact of gender and monthly income on consumer buying behavior. *Journal of International Trade, Logistics and Law*, *9*(1), 241-250.
12. Dev, V.A., & Eden, M.R. (2019). Gradient boosted decision trees for lithology classification. *In Computer Aided Chemical Engineering*, *47*, 113-118. https://doi.org/10.1016/B978-0-12-818597-

1.50019-9
13. Dominici, A., Boncinelli, F., Gerini, F., & Marone, E. (2021). Determinants of online food purchasing: The impact of socio-demographic and situational factors. *Journal of Retailing and Consumer Services, 60*. https://doi.org/10.1016/j.jretconser.2021.102473
14. Donoghue, S., Wilken-Jonker, I., Steffens, F.E., & Kirsten, J.F. (2021). South African consumers' willingness to pay a premium for Karoo Lamb: The influence of subjective and objective knowledge, label information and demographics. *Journal of Retailing and Consumer Services, 63*. https://doi.org/10.1016/j.jretconser.2021.102664
15. Gauri, D.K., Jindal, R.P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., & Howerton, E. (2021). Evolution of retail formats: Past, present, and future. *Journal of Retailing, 97*(1), 42-61. ISSN 0022-4359. https://doi.org/10.1016/j.jretai.2020.11.002
16. Golriz Ziaie, Z., Moghaddasi, R., & Yazdani, S. (2015). Estimation of customer satisfaction index of food markets, Case study: Mashhad Urbanity's Hypermarkets. *Journal of Agricultural Economics and Development, 29*(2), 181-191. ISSN 2008-4722. https://doi.org/10.22067/JEAD2.V0I0.40763
17. Gomes, A. (2018). Influencing factors of consumer behavior in retail shops available at SSRN: https://ssrn.com/abstract=3151879 or http://dx.doi.org/10.2139/ssrn.3151879
18. Greenacre, L., & Akbar, S. (2019). The impact of payment method on shopping behavior among low income consumers. *Journal of Retailing and Consumer Services, 47*, 87-93. https://doi.org/10.1016/j.jretconser.2018.11.004
19. Han, J., Kamber, M., & Pei, J. (2022). Data mining: concepts and techniques, Morgan Kaufmann. https://doi.org/10.1016/B978-0-12-381479-1.00020-4
20. Hanaysha, J. (2018). An examination of the factors affecting consumer's purchase decision in the Malaysian retail market. *PSU Research Review, 2*(1), 7-23. https://doi.org/10.1108/PRR-08-2017-0034
21. Hecht, A.A., Perez, C.L., Polascek, M., Thorndike, A.N., Franckle, R.L., & Moran, A.J. (2020). Influence of food and beverage companies on retailer marketing strategies and consumer behavior. *International Journal of Environmental Research and Public Health, 17*(20), 7381. https://doi.org/10.3390/ijerph17207381
22. Hingley, M., Lindgreen, A., & Chen, L. (2009). Development of the grocery retail market in China: A qualitative study of how foreign and domestic retailers seek to increase market share. *British Food Journal, 111*(1), 44-55. https://doi.org/10.1108/00070700910924227
23. Jofreh, M. (2013). An investigation of business activities in Iran retailing industry. *Research Journal of Applied Sciences, Engineering and Technology 6*(5), 858-861.
24. Kol, O., & Levy, S. (2023). Men on a mission, women on a journey - Gender differences in consumer information search behavior via SNS: The perceived value perspective. *Journal of Retailing and Consumer Services, 75*, 103476. https://doi.org/10.1016/j.jretconser.2023.103476
25. Kotsiantis, S.B. (2013). Decision trees: a recent overview. *Artificial Intelligence Review, 39*(4), 261-283. https://doi.org/10.1007/s10462-011-9272-4
26. Kotu, V., & Deshpande, B. (2018), Chapter 4 – Classification, Data science: concepts and practice (Second Edition), Morgan Kaufmann, 65-163.
27. Kumar, D. (2018). Factors influencing consumers' choice of retail store format in Assam, India. *Journal of Marketing Management, 1*(17), 22-37.
28. Kumar, M.G., Hemanth, K., Gangadhar, N., Kumar, H., & Krishna, P. (2014). Fault diagnosis of welded joints through vibration signals using Naïve Bayes algorithm. *Procedia Materials Science, 5*, 1922-1928. https://doi.org/10.1016/j.mspro.2014.07.514
29. Laine, K. (2014). The factors influencing the choice of grocery store among finnish consumers. Business. ttps://urn.fi/URN:NBN:fi:amk-201405096933
30. Lintang, M., Pandiangan, N., & Hyronimus, D. (2022). Use of the C4.5 Algorithm to Analyze Student Interest in Continuing to College. SHS Web of Conferences.

31. Liyanage, L., PLGSD, P., & Rathnayake, T. (2020). Determinants of consumers' selection of supermarkets for grocery shopping; Empirical Evidence from Western Province, Sri Lanka. In International Conference on Marketing Management.
32. Makgosa, R., & Sangodoyin, O. (2017). Retail market segmentation: the use of consumer decision-making styles, overall satisfaction and demographics. *The International Review of Retail, Distribution and Consumer Research, 28*(1), 64–91. https://doi.org/10.1080/09593969.2017.1334690
33. Manuere, F. (2023). Factors affecting customers' choice of supermarkets for grocery shopping in Chinhoyi Town. *International Journal of Academic Research in Public Policy and Governance, 9*(1), 10–20
34. McHugh, M.L. (2012), Interrater reliability: the kappa statistic. *Biochemia Medica, 22*(3), 276-282.
35. Meng, X., Zhang, P., Xu, Y., & Xie, H. (2020). Construction of decision tree based on C4.5 algorithms for online voltage stability assessment. *International Journal of Electrical Power & Energy Systems, 118,* 105793. https://doi.org/10.1016/j.ijepes.2019.105793
36. Moitra, A.K., Bhattacharya, J., Kayal, J.R., Mukerji, B., & Das, A.K. (2021). Innovative exploration methods for minerals, oil, gas, and groundwater for sustainable development. https://doi.org/10.1016/C2020-0-00590-6
37. Nguyen, T.D.E. (2019). Factors affecting customer loyalty of different strategic groups in the Vietnamese supermarket sector (Doctoral dissertation, University of hull).
38. Nisbet, R., Miner, G.D., & Yale, K. (2018). Chapter 9 – Classification, Nisbet, R., Miner, G. D., & Yale, K., Handbook of statistical analysis and data mining applications. 169-186 in Academic press.
39. Noor, Z. (2020). The effect of price discount and in-store display on impulse buying. *Journal Ilmu-ilmu Sosial dan Humaniora. 22*(2), 133-139. https://doi.org/10.24198/sosiohumaniora.v22i2.26720
40. Ooi, M.P., Sok, H.K., Kuang, Y.C., & Demidenko, S. (2017). Alternating decision trees. In P. Samui, S. S. Roy, & V. E. Balas (Eds.), Handbook of Neural Computation. PP 345-371 in Academic Press.
41. Pandey, A., & Kaur, D.A. (2018). A comprehensive study on evolution, present scenario and future prospects of retailing. *International Journal of Current Research in Life Sciences, 7*(2), 1158-1162.
42. Quinlan, J.R. (1996). Improved use of continuous attributes in C4.5. *Journal of Artificial Research, 4,* 77–90. https://doi.org/10.48550/arXiv.cs/9603103
43. Quinlan, J.R. (2014). C4.5: Programs for Machine Learning. 58-60. https://books.google.com/books/about/C4_5.html?id=b3ujBQAAQBAJ
44. Rahim, M.A., Mushafiq, M., Khan, S., & Arain, Z.A. (2021). RFM-based repurchase behavior for customer classification and segmentation. *Journal of Retailing and Consumer Services, 61*. https://doi.org/10.1016/j.jretconser.2021.102566
45. Ram, S. (2022). Data Mining. Computer Sciences. from Encyclopedia.com: https://www.encyclopedia.com/computing/news-wires-white-papers-and-books/data-mining
46. Rasheed, A., Shahid Yaqub, R., & Baig, F. (2018). Factors affecting impulse buying behaviors in shopping malls: Evidence from Bahawalpur Region, Pakistan. *Journal of Marketing and Consumer Research. 39.*
47. Razu, M.A., & Roy, D. (2019). Prominent factors influencing consumers' choice of retail store. *Journal of Business and Management, 21*(6), 62-66. https://doi.org/10.9790/487X-2106026266
48. Reddy, G.S., & Chittineni, S. (2021). Entropy based C4.5-SHO algorithm with information gain optimization in data mining. *Peer Journal Computer Science, 7*. https://doi.org/10.7717/peerj-cs.424

49. Roy, G., Debnath, R., & Mitra, P.S. (2021). Analytical study of low-income consumers' purchase behaviour for developing marketing strategy. *International Journal Syst Assur Engineering Management, 12*, 895–909. https://doi.org/10.1007/s13198-021-01143-6
50. Savaşkan, A., & Çatı, K. (2021). Investigation of consumer behavior in market shopping in the gender context. *Elektronik Sosyal Bilimler Dergisi, 20*(77), 255-272. https://doi.org/10.17755/esosder.767017
51. Shamsher, R. (2016). Store image and its impact on consumer behavior. *Elk Asia Pacific Journal of Marketing and Retail Management, 7*, (2), 1-27. ISSN 0976-7193. https://www.researchgate.net/project/STORE-IMAGE-AND-ITS-IMPACT-ON-CONSUMER-BEHAVIOR
52. Šostar, M., & Ristanović, V. (2022). Assessment of influencing factors on consumer behavior using the AHP model. *Sustainability, 15*(13), 10341. https://doi.org/10.3390/su151310341
53. Sugumaran, V., & Ramachandran, K.I. (2007). Automatic rule learning using decision tree for fuzzy classifier in fault diagnosis of roller bearing. *Mechanical Systems and Signal Processing, 21*, 2237–2247. https://doi.org/10.1016/j.ymssp.2006.09.007
54. Sun, K., Likhate, S., Vittal, V., Kolluri, V.S., & Mandal, S. (2007). An online dynamic security assessment scheme using phasor measurements and decision trees. *IEEE Transactions on Power Systems, 22*(4), 1935-1943. https://doi.org/10.1109/TPWRS.2007.908476
55. Taylor, M.J., Kwasnica, V., Reilly, D., & Ravindran, S. (2019). Game theory modelling of retail marketing discount strategies. *Marketing Intelligence and Planning, 37*(5), 555-566. ISSN 0263-4503.
56. Terano, R., Yahya, R., Mohamed, Z., & Saimin S. (2015). Factor influencing consumer choice between modern and traditional retailers in Malaysia. *International Journal of Social Science and Humanity, 5*(6). https://doi.org/10.7763/IJSSH.2015.V5.509
57. Thakur, P., Mehta, P., Devi, C., Sharma, P., Singh, K.K., Yadav, S., Lal, P., Raghav, Y.S., Kapoor, P., & Mishra, P. (2023). Marketing performance and factors influencing farmers choice for agricultural output marketing channels: The case of garden pea (*Pisum sativum*) in India. *Frontiers in Sustainable Food Systems, 7*, 1270121. https://doi.org/10.3389/fsufs.2023.1270121
58. Tian, X., Cao, S., & Song, Y. (2021). The impact of weather on consumer behavior and retail performance: Evidence from a convenience store chain in China. *Journal of Retailing and Consumer Services, 62*. https://doi.org/10.1016/j.jretconser.2021.102583
59. Veeck, A., & Veeck, G. (2000). Consumer segmentation and changing food purchase patterns in Nanjing", PRC. *World Development, 28*(3), 457-471. https://doi.org/10.1016/S0305-750X(99)00135-7
60. Vindigni, G., Peri, I., Consentino, F., Selvaggi, R., & Spina, D. (2022). Exploring consumers attitudes towards food products derived by new plant breeding techniques. *Sustainability, 14*(10). https://doi.org/10.3390/su14105995
61. Walkinshaw, N. (2013). Reverse-engineering software behavior, Memon, A., Advances in Computers PP 1-58 in Elsevier.
62. Yildirim, K., Cagatay, K., & Hidayetoğlu, M.L. (2015). The effect of age, gender and education level on customer evaluations of retail furniture store atmospheric attributes. *International Journal of Retail & Distribution Management, 43*(8), 712-726. https://doi.org/10.1108/IJRDM-01-2013-0034
63. Zaki, M.J., & Meira, W. (2020). *Data mining and machine learning: Fundamental concepts and algorithms*. Cambridge University Press.
64. Zulqarnain, H., Zafar, A.U., & Shahzad, M. (2015). Factors that affect the choice of consumers in selecting retail store, for grocery shopping. *International Journal of Multidisciplinary and Current Research, 3*(1), 1167-1172S. http://ijmcr.com

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جلد ۳۸، شماره ۴، زمستان، ۱۴۰۳، ص. ۳۷۰-۳۵۱

رویکرد داده کاوی برای انتخاب بازار خرده‌فروشی مصرف‌کنندگان: مطالعه موردی بازارهای خرده‌فروشی شهری در ایران

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تاریخ دریافت: ۱۴۰۳/۰۲/۳۱

تاریخ پذیرش: ۱۴۰۳/۰۴/۱۸

چکیده

بازارهای خرده‌فروشی شهری، بازارهای خرده‌فروشی دولتی هستند که اخیراً در ایران با هدف افزایش رفاه مصرف‌کنندگان و تولیدکنندگان تأسیس شده‌اند. برای دستیابی به این هدف و گسترش حضور در بخش خرده‌فروشی شهری، درک جامعی از رفتار مصرف‌کننده در این بازارها ضروری است. این مطالعه با استفاده از الگوریتم C4.5 به بررسی عوامل مختلف اجتماعی-اقتصادی مؤثر بر تصمیم‌گیری مصرف‌کنندگان در بازارهای خرده‌فروشی پرداخته است. داده‌ها از طریق نظرسنجی از ۱۸۹ مصرف‌کننده با استفاده از روش نمونه‌گیری تصادفی در شهر مشهد در سال‌های ۱۳۹۸ و ۱۳۹۹ جمع‌آوری شد. نتایج نشان داد که آگاهی از تخفیف‌های موجود به‌طور قابل توجهی انتخاب مصرف‌کننده را در بازارهای خرده‌فروشی شهری تحت تأثیر قرار می‌دهد. با این حال، علی‌رغم تخفیف‌های موجود، آگاهی در میان مصرف‌کنندگان پایین است که نیاز به بازنگری در استراتژی‌های تبلیغاتی می‌باشد. همچنین نتایج نشان داد تجربه خرید از بازارهای شهری، درآمد خانوار و تحصیلات از جمله عوامل تأثیرگذار بر انتخاب مصرف‌کننده می‌باشند. یافته‌های این مطالعه می‌تواند بینش‌های ارزشمندی برای سیاست‌گذاران و سهامداران فراهم آورد که در پی افزایش اثربخشی بازارهای خرده‌فروشی محلی در ایران هستند. علاوه بر این، با بهره‌گیری از این بینش‌ها در زمینه رفتار مصرف‌کننده و پویایی بازار، این بازارها می‌توانند رونق گرفته و نقش بسزایی در بهبود بخش خرده‌فروشی و اقتصاد ایران ایفا کنند. در این راستا، توصیه‌هایی مانند کمپین‌های تبلیغاتی، استراتژی‌های آموزش‌محور، همکاری با تولیدکنندگان محلی و سیاست‌های بازاریابی فراگیر با هدف بهبود دسترسی همه مصرف‌کنندگان به بازارهای خرده‌فروشی شهری ارائه گردید.

واژه‌های کلیدی: داده کاوی، درخت تصمیم، رفتار مصرف کننده، یادگیری ماشین

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https://doi.org/10.22067/jead.2024.88151.1269

Journal of Agricultural Economics & Development

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

Research Article
Vol. 38, No. 4, Winter 2025, p. 371-391

Investigating the Effective Components on Customer Lifetime Value of Dairy Products in Tehran

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Received: 17-08-2024
Revised: 02-10-2024
Accepted: 19-10-2024
Available Online: 29-10-2024

How to cite this article:
Vajdi Hokm Abad, F., Rafiee, H., Chizari, A.H., Yazdani, S., & Hosseini, S.S. (2025). Investigating the effective components on customer lifetime value of dairy products in Tehran. *Journal of Agricultural Economics & Development*, *38*(4), 371-391. https://doi.org/10.22067/jead.2024.89411.1290

Abstract

In contemporary marketing, maintaining and enhancing customer loyalty toward a company's products or services has become a primary focus. Among the factors influencing customer loyalty is ethical marketing, a field of applied ethics related to the principles governing behavior, advertising, and regulation in marketing. Over the past two decades, ethical consumerism has grown in importance due to increasing social and environmental concerns. This study examines the impact of ethical components on Customer Lifetime Value (CLV) for dairy product consumers in Tehran in 2023. A total of 710 questionnaires were completed, and the GWRFM method was employed to extract the necessary information for calculating CLV. The results revealed a high frequency of clusters with low lifetime value. In the subsequent phase, multinomial logit regression was utilized to analyze the effect of ethical components on CLV, highlighting the significant positive impact of adherence to industry regulations and acceptance of social responsibility. Therefore, it is recommended that stakeholders in the dairy industry assure customers of their compliance with regulations and social responsibility to elevate them to higher-value clusters and foster loyalty. By respecting ethical norms, a substantial portion of consumers of cheese, yogurt, and ayran products may transition toward becoming valuable customers in this sector.

Keywords: Customer lifetime value, Ethical marketing, Ethical consumerism, GWRFM

https://doi.org/10.22067/jead.2024.89411.1290

Introduction

Customer loyalty is defined as a preference for a brand over others, accompanied by a psychological commitment. In today's hyper-competitive environment, organization cannot succeed without addressing customer needs and desires and ensuring their satisfaction. Research indicates that perceived customer value significantly influences customer satisfaction, loyalty, and the successful sale of goods or services, often more than the characteristics of the goods themselves (Zehir, & Narcıkara, 2016). Customer loyalty has gained special importance, particularly in the service sector, due to competitive pressures. Scholars define customer loyalty as favorable attitudes toward services/products and a commitment to their purchase or use (Shiri *et al*., 2017). Increased loyalty can stabilize revenue streams and enhance profitability over time. Without customer loyalty, even the best business models falter. Organizations strive to continuously meet customer expectations and cultivate long-term relationships. Loyalty reflects a favorable attitude toward a business, leading to repeat purchases (Niazian, 2018). Ethical marketing is known as a factor that can enhance customer loyalty, which pertains to the ethical principles governing behavior, advertising, and regulation in marketing. To sustainably attract buyers, companies must instill confidence in the honesty and correctness of their product advertisements. This concept has been widely discussed in management and marketing literature (Jandaghi *et al*., 2017).

Research on ethical judgment indicates that moral feelings significantly drive cognitive reasoning processes before conscious ethical reasoning occurs (Haidt, 2007; Greene & Haidt, 2002). Neuroimaging studies confirm that specific brain areas related to emotional feelings activate in response to ethical dilemmas (Moll *et al*., 2005; Moll *et al*., 2002). Ethical consumerism has become increasingly significant over the last two decades due to social and environmental issues (Adams, 2002). More consumers are integrating ethical considerations into their purchasing decisions, such as opting for environmentally labeled products or avoiding ethically questionable items. Various studies demonstrate that responsible corporate behavior positively affects brand reputation, employer image, investor access, and competitive positioning (Chang, 2011). Many retailers are now offering ethical products under private labels (Willer, & Lernoud, 2016). Pecoraro *et al*. (2014) describe ethical consumption as a behavioral pattern prompting consumers to reconsider their everyday choices from an ethical standpoint. Crane & Matten (2010) define ethical consumption as the deliberate choice to engage in certain consumption practices based on personal ethical beliefs and values. Shaw *et al*. (2016) view ethical consumption as embodying care, responsibility, and commitment, including consumers' willingness to pay extra for sustainable products (Tsarenko *et al*., 2013).

In the context of consumers and retailing, terms like ethical, conscious, environmentally friendly, green consumption, and slow consumption are often used interchangeably. Green consumption relates consumerism to its environmental effects (Glim *et al*., 2013). Organic food consumption, often associated with health awareness, is another ethical consumption pattern (Rana & Paul, 2017).

Among the methods for measuring and profiling customer loyalty, the Customer Lifetime Value (CLV) method is noteworthy for identifying the most valuable customers and calculating customer value (Kumar *et al*., 2009; Fader, 2012). CLV plays a vital role in customer retention and long-term relationships, key goals of CRM (Haenlein, 2017). Each customer is an asset with unique preferences, and companies compete for their attention. Customers vary in needs, expectations, and behaviors, necessitating tailored management approaches (Monalisa, 2018). Marketing's customer-centered focus drives organizations to understand the real value of customers. Some researchers argue that CLV is the most effective variable for measuring customer value. However, CLV's meaning varies across industries and is influenced by the types of

services and products offered. The CLV method connects the value provided by the company to the customer and the value the customer contributes to the company over their relationship (Buttle & Maklan, 2016). Most studies in the literature have utilized CLV for segmentation (Yoseph *et al.*, 2019; Akhondzadeh *et al.*, 2014), resulting in segments reflecting only customer value (e.g., high profit, low profit) without detailing specific industry characteristics (Mosaddegh *et al.*, 2021). The primary goal and application of CLV is customer segmentation (Abens & Parcheta, 2016).

This study focuses on calculating the customer lifetime value as a representation of customer loyalty to dairy products and the relationship between CLV and ethical components. To calculate CLV and segment dairy product consumers, the K-means clustering method and WRFM method were employed, and multinomial logit regression used to measure the impact of ethical components on clustering.

Methodology

The CLV-based segmentation model allows a company to identify the most profitable customer groups, understand their common characteristics, and focus more on them. This process is based on current value, potential value, and loyalty while also considering generated profit share and potential profit. However, these factors can only be calculated if the customer has a long-term relationship with the business entity (Abens & Parcheta, 2016).

According to Gupta *et al.*, 2006; Estrella-Ramón *et al.*, 2013; Jasek *et al.*, 2018 and Jasek *et al.*, 2019, there are two approaches for analyzing CLV components: the deterministic approach and the stochastic approach (a combination of six different modeling methods). The deterministic approach uses equations in which all criteria are directly incorporated into the simplified CLV calculation. One of the representatives of this approach is the RFM model (Recency, Frequency, Monetary). The RFM analysis model, which is one of the most powerful and simplest CLV models for customer loyalty, was proposed by Hughes (1994). Customer loyalty is an appropriate feature for customer segmentation. Customers' past purchasing behavior can indicate their level of loyalty (Chang & Tsai, 2011). The RFM model measures when, how often, and how much a customer has purchased (Winer, 2001). This model, using three features-recency (the time since the last purchase), frequency (the number of purchases in a given time period), and monetary value (the amount spent in the last period)—distinguishes important customers from a dataset (Monalisa *et al.*, 2019). RFM analysis is used to calculate a score for each customer (Yeh *et al.*, 2009). In more complex scenarios, weights are used to assign more or less importance to the RFM variables (Kasperova, 2020).

In this study, RFM variables are used as inputs for other models. Given that segmentation based on products is one of the objectives of this study, the model used to calculate customer lifetime value is the Group WRFM model. This model extracts the values of the three variables R, F, and M for each of the products that customers have purchased so far. To do this, products must first be grouped, and then customer transactions must be considered separately for each group of products to calculate WRFM values for each purchased product category. Using this model, a precise sales strategy can be developed to better meet market needs. Therefore, customer segmentation is based on purchased products. After extracting the model variables, they were scaled to calculate each customer's score. Since the range of variables differs based on their nature and to prevent larger values from dominating the analysis, a normalization process must be conducted. This ensures that the data are comparable on a uniform scale. In this stage, the min-max approach is used.

Next, the weight of each parameter must be determined for ranking and clustering customers. In this study, the Analytic Hierarchy Process (AHP) and expert opinions are employed for weighting the indicators, while the Expert Choice software is used to determine

parameter weights. In the following stage, customers are ranked based on their Customer Lifetime Value (CLV) using the following relationships (Kasperova, 2020).

$$CLVci = (NR\text{Milk}ci \times WR) + (NF\text{Milk}ci \times WF) + (NM\text{Milk}ci \times WM) \quad (1)$$

$$CLVci = (NF\text{Cheese}ci \times WF) + (NR\text{Cheese}ci \times WR) + (NM\text{Cheese}ci \times WM) \quad (2)$$

$$CLVci = (NF\text{Yogurt}ci \times WF) + (NR\text{Yogurt}ci \times WR) + (NM\text{Yogurt}ci \times WM) \quad (3)$$

$$CLVci = (NF\text{Ayran}ci \times WF) + (NR\text{Ayran}ci \times WR) + (NM\ \text{Ayran}ci \times WM) \quad (4)$$

In the relationship described above, NRMilk denotes the normalized value of RNMilk within cluster ci, while WR represents the weight of parameter R. Other parameters are defined in a similar manner.

Since loyalty is a multi-level variable based on the categorization of customer lifetime value, the multinomial logit model can be used to evaluate the impact of each ethical factor on loyalty. This approach relies on the assumption that the levels are independent and that excluding one level when selecting individuals for the chosen loyalty categories does not lead to any changes (Long, 1997). For the purposes of this study, the multinomial logit model was applied to examine the effect of ethical factors on customer lifetime value, which was categorized into five levels: very high, high, medium, low, and very low. In the multinomial logit model, one category of the dependent variable is selected as the reference class. In other words, the probability of selecting one category of the dependent variable relative to the reference class is evaluated (Ben-Akiva & Lerman, 1985). The general structure of the multinomial logit model is expressed by the following equation:

$$\text{, M=0,1,2,} \quad (5)$$

The observed dependent variable consists of four loyalty groups for consumer iii. wiw_iwi represents the vector of explanatory variables, and αm\alpha_mαm is a vector of model coefficients. mmm denotes each consumer group. The first step in estimating multinomial logit models is to designate one group from the dependent variable categories as the reference group, so that the probability of selecting the other groups relative to it can be measured. Given that logit models are discrete choice models, the estimation process utilizes the logarithm of the likelihood function:

(6)

n the model estimated in this study, the dependent variable consists of customer value clusters, calculated using equations 1 to 4 (divided into five categories: very high-value customers, high-value customers, medium-value customers, low-value customers, and very low-value customers). The explanatory variables include the three ethical components previously mentioned. In this model, the coefficients are not directly interpreted because the change in probability resulting from an increase in an independent variable depends not only on its own value but also on the values of other variables. Since this probability change is not constant, the coefficients themselves are not directly meaningful. Instead, only the sign of the coefficient is interpreted, as it indicates the direction of the probability change. After estimating the model, the Relative Risk Ratio (RRR) criterion is calculated to determine the impact of each explanatory variable on the dependent variable groups (willingness to purchase more). This criterion measures how the probability of selecting the comparison group, relative to the probability of selecting the reference group, changes with a change in the explanatory variable (Long, 1997).

To assess the goodness-of-fit of the multinomial logit model, several tests and criteria are used, including pseudo-R2R^2R2 statistics. These statistics do not have an interpretation equivalent to the regular R2R^2R2, and it can only be stated that the value increases with the power of model fit (Greene, 2011). In the multinomial logit model, to examine the effect of independent variables on the dependent variable, two tests-Likelihood

Ratio (LR) and Wald-are used for each of the independent variables in the model (Isengildina & Hudson, 2001).

To test the Independence of Irrelevant Alternatives (IIA) assumption, the Hausman test is recommended. To test the assumption of independence of irrelevant alternatives, the Hausman test is recommended (Hausman & McFadden, 1984).

The population under study in this research consists of consumers of dairy products (milk, cheese, yogurt, and ayran) in Tehran, Iran. A sample size of 620 questionnaires was initially determined. An electronic version of the questionnaire was created, and the link was distributed to residents of Tehran. In addition to the online completion of the questionnaire, in-person interviews were also conducted. Ultimately, to ensure the reliability of the data and minimize errors, 710 valid questionnaires were included for analysis after excluding incomplete responses. To gather insights from both consumers and experts (specialists in the private dairy industry), a combination of accessible random sampling and snowball sampling methods was employed.

Results and Discussion

The demographic characteristics of the studied individuals are illustrated in Fig. 1 and 2. As shown in the charts, 55.9% of consumers are women, while 44.1% are men. The respondents have an average age of 35, ranging from 18 to 60 years. The highest percentage belongs to individuals with a bachelor's degree (approximately 46.9%), whereas the lowest percentage corresponds to those with a doctoral degree or higher. Regarding employment status, about 41% of consumers are employed, while the unemployed group has the lowest representation at 4.2%.

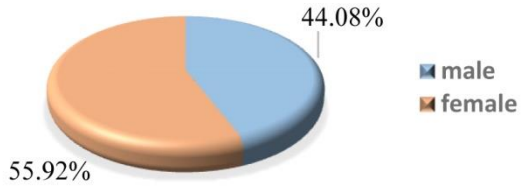

Figure 1- The percentage of Gender frequency

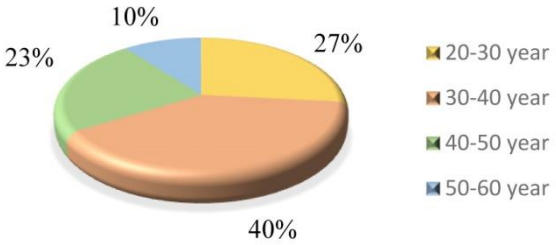

Figure 2- The percentage of age frequency

In the initial step of calculating Customer Lifetime Value (CLV), the RFM model parameters, derived from 710 completed questionnaires, were normalized and subsequently categorized into five clusters using the K-Means clustering method. The optimal number of clusters was determined using the Dunn index, based on the clustering results analyzed with SPSS Statistics 25. The average values of the R, F, and M parameters for each dairy product within each cluster are presented in Table 1.

Table 1- Member clustering results based on RFM parameters for each product

(Cluster)	Milk			Cheese			Yogurt			Ayran		
	R	F	M	R	F	M	R	F	M	R	F	M
1	1	0.206	0.931	1	0	0	0.165	0.31	0.945	0.853	0.043	0.210
2	0.158	0.052	0.781	0.19	0	0	0.733	0.107	0.878	0.881	0.035	0.815
3	0.317	1	1	0.239	0.102	0.857	0.092	0.053	0.79	0.306	0.002	0.174
4	0.092	1	0.985	0.147	1	1	0.375	0.077	0.869	0.981	1	0.16
5	0.173	0.287	0.949	1	0.103	0.869	0.119	0.099	0.951	0.530	4	0.206

Source: Researcher's Calculations

To determine the weight of each parameter, a similar approach was used by consulting ten experts from the private dairy industry. The weights were calculated using the AHP method and analyzed with Expert Choice software, with the results presented in Table 2. The total sum of the weights equals one, and the AHP consistency index was found to be 0.02.

Next, Equations 1 to 4 were applied to calculate the CLV score for each cluster using the WRFM method. The CLV values and the corresponding rankings for each cluster are presented in Table 3.

Table 2- RFM model parameter weights

R	F	M	Parameter
0.11	0.245	0.645	Weight

Source: Researcher's Calculations

Table 3- CLV calculation results and cluster ranking for each product

Cluster	Milk			Cheese			Yogurt			Ayran		
	CLV	Rank	Status of indicators	CLV	Rank	Status of indicators	CLV	Rank	Status of indicators	CLV	Rank	Status of indicators
1	0.761	3	↓↓↑	0.11	4	↑↓↓	0.704	1	↑↑↑	0.584	4	↑↑↓
2	0.537	5	↓↓↓	0.02	5	↓↓↓	0.673	2	↑↑↓	0.666	3	↑↓↑
3	0.924	1	↑↑↑	0.604	3	↓↓↑	0.532	5	↓↓↓	0.216	5	↓↓↓
4	0.89	2	↑↓↑	0.906	1	↑↑↑	0.62	4	↑↓↓	0.895	2	↑↑↓
5	0.702	4	↑↓↓	0.693	2	↑↑↓	0.651	3	↑↓↑	1.344	1	↑↑↑

Source: Researcher's Calculations

In analyzing the indicator status, the average value of each RFM model parameter for each product within each cluster was compared to the overall average across the dataset. This comparison highlights how each cluster's parameter values deviate from the general trend. If a parameter's average value in a cluster exceeds the overall average, it is marked with an upward arrow (↑) to indicate a favorable status, whereas a lower-than-average value is denoted by a downward arrow (↓) to reflect an unfavorable status.

The frequency and distribution of customers across Customer Lifetime Value (CLV) categories are presented in Fig. 3 for milk, Fig. 4 for cheese, Fig. 5 for yogurt, and Fig. 6 for Ayran. The results indicate that the proportion of customers with very high and high loyalty is relatively low. For milk, yogurt, and Ayran, the highest frequency percentages correspond to very low and low loyalty levels, respectively. In contrast, for cheese, the majority of customers are classified within the medium loyalty cluster.

To examine the impact of ethical consumption factors on customer loyalty and their distribution across customer lifetime value clusters, a multinomial logit model was employed. The ethical consumption factors were selected based on prior research in ethics, marketing, and consumer behavior, as these

aspects are expected to influence customer placement within different lifetime value clusters. These factors include the brand's compliance with industry regulations, adherence to ethical norms, and customer preference for brands that demonstrate social responsibility. Each of these components was measured on a five-point Likert scale, where a score of 5 represents "strongly agree" and 1 signifies "strongly disagree."

Fig. 7, 8, and 9 show the frequency distribution of responses for each ethical factor, respectively, indicating that customers place significant importance on ethical considerations. However, the extent to which these factors influence purchasing decisions, as well as their impact on loyalty and customer lifetime value, remains an open question that will be further explored through multinomial logit analysis. The first step in estimating the multinomial logit model is to designate one of the groups as the base group, enabling the calculation of the probability of selecting other groups relative to this reference category. Typically, the group with the highest frequency is chosen as the base group. The results of the multinomial logit model for each product are presented separately below.

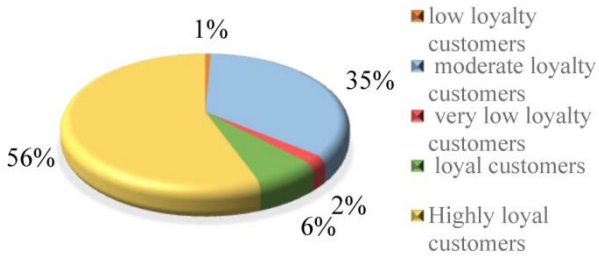

Figure 3- Percentage frequency of customer lifetime value clusters (Milk)

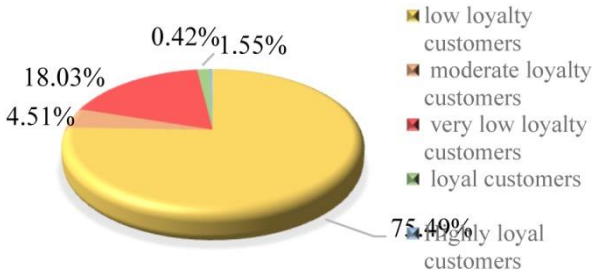

Figure 4- Percentage frequency of customer lifetime value clusters (cheese)

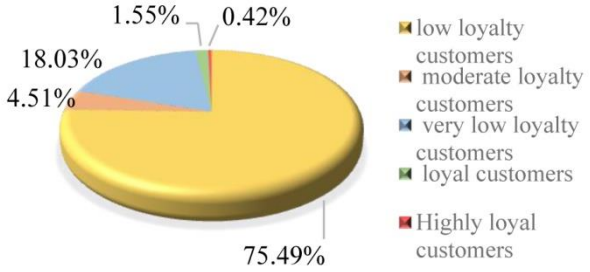

Figure 5- Percentage frequency of customer lifetime value clusters (ayran)

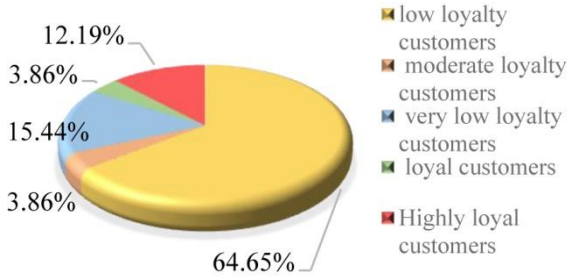

Figure 6- Percentage frequency of customer lifetime value clusters (yogurt)

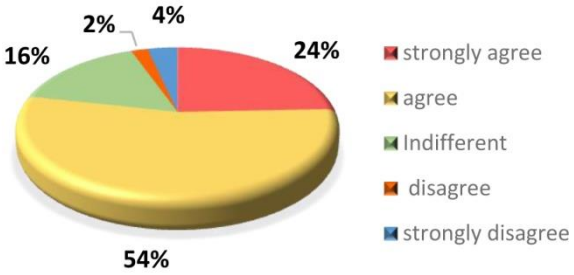

Figure 7- The frequency percentage of items in the second component

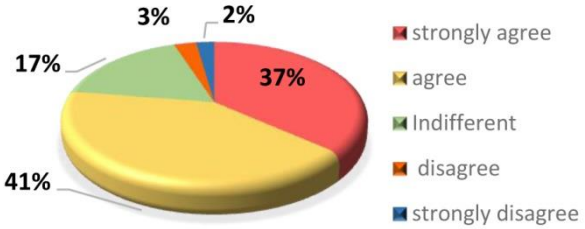

Figure 8- The frequency percentage of items in the first component

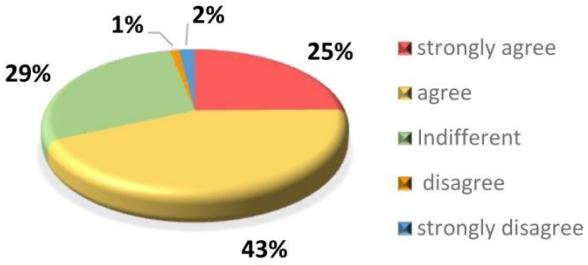

Figure 9- Frequency percentage of items in the third component

Product: Milk

In this study, the fourth cluster, consisting of individuals with low customer lifetime value, was designated as the base group for segmenting customers of the milk product. To ensure the optimal and accurate classification of the dependent variable groups, the Wald test was conducted, with the results presented in Table 4. The statistical analysis of pairwise comparisons between the first and third clusters showed no significant differences, meaning the null hypothesis could not be rejected. Consequently, the first cluster was merged with the second, while the third cluster was combined with the fourth. After repeating the test, all pairwise comparisons yielded significant results, confirming that the three customer lifetime value clusters should remain

distinct and should not be merged into a single group.

Table 4- Parent test results for combining loyalty levels (milk)

Clusters	Wald Test	
	Stat	Probe
Very high & high loyalty people with medium & low loyalty	27.325	0.00
People with very low loyalty to people with medium and low loyalty	18.291	0.00
People with very high and high loyalty with people with very low loyalty	27.954	0.00

Researcher's Calculations

The generalized Hausman test was employed to evaluate the independence of irrelevant alternatives within the model, with the results presented in Table 5. According to this Table, the statistical values for all groups are insignificant, indicating that the null hypothesis regarding the independence of irrelevant alternatives cannot be rejected. Therefore, it can be concluded that the groups are independent of one another, and use of the multinomial logit model for this analysis is appropriate and will not pose any issues.

Table 5- The results of the generalized Hausman test for the assumption of independence of unrelated options (IIA) (milk)

clusters	Stat	Probe
people with Very high & high loyalty	-0.792	1.00
people with medium and low loyalty	-6.523	1.00
people with very low loyalty	-10.007	1.00

The goodness of fit for the regression model is presented in Table 6, where the likelihood ratio of the estimated model is reported as 82.805. Given the significance level of 0.00, this result is statistically significant. Therefore, the overall significance of the likelihood ratio test confirms the appropriateness of the regression model.

Table 6- Good fit criteria of the multinomial logit model (milk)

Statistics	Statistics value	Statistics	Statistics value
LR	-657.304	Pseudo R2	0.078
LR-prob	0	Cragg & Uhler's R2	0.128
LR(6)	82.805	AIC	1354.608
McFadden's Adj R2	0.033	BIC	-4.056

Researcher's Calculations

The results of estimating the multinomial logit model using the maximum likelihood method to assess the impact of the specified explanatory variables on customer loyalty for the milk product (measured by the CLV score) are presented in Table 7. It is important to note that the estimated coefficients indicate only the magnitude and direction of their effect on the odds ratio. The relative odds ratio represents the change in the odds of belonging to a specific group compared to the base group in response to variations in the explanatory variables.

The importance individuals place on adhering to ethical norms has a significant negative effect on the likelihood of being classified in the high and very high customer lifetime value clusters compared to the base cluster (very low customer lifetime value), reducing the odds of inclusion in this group by 67.0%. In contrast, the emphasis on social responsibility has a significant positive impact, increasing the likelihood of being categorized in the high and very high customer lifetime value clusters by 396.0% relative to the base cluster. Additionally, individuals who prioritize compliance with industry regulations exhibit a significant negative effect on the likelihood of being classified in the medium customer lifetime value cluster compared to the base cluster, decreasing the odds of inclusion in this group by 62.0%.

Table 7- Estimation results of multinomial logit model (milk)

Category	Variable Name	Coefficient	Standard deviation	P-Value	Relative Risk Ratio
Cluster1 People with a very high & high level of loyalty	Adherence of the brand to the rules of its field of activity	-0.315	0.199	0.114	0.729
	Respect for ethical norms by the brand	-0.390	0.229	0.089	0.676
	preferably a brand with social responsibility	1.37	1.001	0	3.96
Clusterv2 People with an average level of loyalty	Adherence of the brand to the rules of its field of activity	-0.473	0.119	0	0.622
	Respect for ethical norms by the brand	0.217	0.142	0.127	1.242
	preferably a brand with social responsibility	-4.049	0.432	0.694	0.951

Researcher's Calculations

Product: Cheese

For the customer group associated with the cheese product, the third cluster, representing individuals with medium customer lifetime value, was designated as the base group. The Wald test results for pairwise comparisons among all clusters were not statistically significant. Consequently, the first and second clusters were merged, as well as the fourth and fifth clusters. The test was then repeated, with the results presented in Table 8. The findings indicate that the customer lifetime value clusters remain statistically distinct and should not be combined.

Table 8- Parent test results for combining loyalty levels (cheese)

Clusters	Wald Test	
	Stat	Probe
Very high & high loyalty people with medium loyalty people	47.01	0.00
People with very low loyalty & low with people with medium loyalty	24.974	0.00
People with very high & high loyalty versus people with very low & low loyalty	40.372	0.00

Researcher's Calculations

The generalized Hausman test was employed to evaluate the independence of irrelevant alternatives within the model, with the results presented in Table 9. The statistical values of the test for each group in the model are not statistically significant. Therefore, it can be concluded that the loyalty levels are independent of one another, confirming the appropriateness of the multinomial logit model for this analysis.

Table 9- The results of the generalized Hausman test for the assumption of independence of unrelated options (IIA) (cheese)

Clusters	Stat	Probe
Very high & high loyalty people	-6.829	1.000
People with medium loyalty	-645.415	1.000
people with very low & low loyalty	0.868	0.929

Researcher's Calculations

The goodness of fit for the regression model is presented in Table 10, where the likelihood ratio of the estimated model is reported as 121.65. Given a significance level of less than 1%, this result is statistically significant. Therefore, based on the overall likelihood ratio test, the regression model is considered statistically valid and appropriate for analysis.

Table 10- Good fit criteria of the multinomial logit model (cheese)

Statistics	Statistics value	Statistics	Statistics value
LR	-260.283	Pseudo R2	0.189

LR-prob	0	Cragg & Uhler's R2	0.265
LR(6)	121.65	AIC	544.566
McFadden's Adj R2	0.152	BIC	-82.275

Researcher's Calculations

The results of estimating the multinomial logit model using the maximum likelihood method to assess the impact of the specified explanatory variables on customer loyalty for the cheese product are presented in Table 11. The findings indicate that individuals who prioritize compliance with industry regulations have a significant negative effect on the likelihood of being categorized in the second cluster compared to the base cluster, reducing the probability of inclusion in this group by 0.10%. Furthermore, the importance placed on social responsibility has a significant positive impact on the likelihood of being classified in the high and very high customer lifetime value clusters relative to the base cluster (medium customer lifetime value), increasing the probability of inclusion in this group by 5.49%.

Additionally, adherence to ethical norms has a dual effect: it significantly reduces the likelihood of belonging to the high and very high customer lifetime value clusters while significantly increasing the likelihood of being placed in the very low and low customer lifetime value clusters. Specifically, it decreases the probability of inclusion in the high and very high customer lifetime value clusters by 0.51% and increases the probability of being in the very low and low customer lifetime value clusters by 21.22% compared to the base cluster.

Table 11- Estimation results of multinomial logit model (cheese)

Category	Variable Name	Coefficient	Standard deviation	P-Value	Relative Risk Ratio
Cluster1 People with a very high & high level of loyalty	Adherence of the brand to the rules of its field of activity	-0.179	0.188	0.341	0.835
	Respect for ethical norms by the brand	-0.668	0.196	0.001	0.512
	preferably a brand with social responsibility	1.704	0.25	0.00	5.498
Cluster 2 people with very low & low loyalty	Adherence of the brand to the rules of its field of activity	-2.240	0.438	0.00	0.106
	Respect for ethical norms by the brand	3.055	1.109	0.006	21.221
	preferably a brand with social responsibility	-0.745	0.728	0.306	0.474

Researcher's Calculations

Product: Yogurt

In this study, the fifth cluster of the dependent variable, representing individuals with very low customer lifetime value, was designated as the base group for the yogurt product customer segment. To ensure the optimal and accurate classification of the dependent variable groups, the Wald test was employed, and the results are presented in Table 12. The statistical values for the pairwise comparisons among all clusters were found to be significant. As a result, the null hypothesis, which suggested that the groups could be combined, was rejected. Therefore, the model, with the five distinct levels of the dependent variable, is considered to fit the data appropriately.

The generalized Hausman test was conducted to evaluate the independence of irrelevant alternatives within the model, with the results presented in Table 13. The statistical values for each group in the model were found to be insignificant, confirming the suitability of the multinomial logit model for this analysis.

Table 12- Parent test results for combining loyalty levels (Yogurt)

Category	Wald Test		Category	Wald Test	
	Stat	Probe		Sta	Probe

People with very high loyalty with people with high loyalty	42.227	0.00	High-loyalty people versus low-loyalty people	27.181	0.000
People with very high loyalty versus people with moderate loyalty	35.274	0.00	People with high loyalty versus people with very low loyalty	29.439	0.000
High-loyalty people versus low-loyalty people	20.858	0.00	People with moderate loyalty versus people with low loyalty	41.721	0.000
People with very high loyalty versus people with very low loyalty	40.522	0.00	People with moderate loyalty and people with very low loyalty	9.991	0.019
People with high loyalty versus people with medium loyalty	32.951	0.00	People with low loyalty versus people with very low loyalty	27.386	0.000

Researcher's Calculations

Table 13- The results of the generalized Hausman test for the assumption of independence of unrelated options (IIA) (Yogurt)

Clusters	Stat	Probe
People with very high loyalty	-0.669	1.00
People with high loyalty	-2.949	1.00
People with moderate loyalty	0.978	1.00
people with low loyalty	2.961	0.94
people with very low loyalty	11.785	0.16

Researcher's Calculations

The goodness of fit for the regression model is presented in Table 14, where the likelihood ratio of the estimated model is 110.03. Given the significance level of less than 1%, this result is statistically significant. Therefore, the regression model is considered significant overall.

Table 14- Good fit criteria of the multinomial logit model (Yogurt)

Statistics	Statistics value	Statistics	Statistics value
LR	-916.406	Pseudo R2	0.056
LR-prob	0	Cragg & Uhler's R2	0.154
LR(12)	110.03	AIC	1872.778
McFadden's Adj R2	0.036	BIC	-31.25

Researcher's Calculations

The results of estimating the multinomial logit model using the maximum likelihood method to assess the impact of the specified explanatory variables on customer loyalty for the yogurt product are presented in Table 15. Individuals who prioritize compliance with industry regulations have a significant positive effect on the likelihood of being classified in the second cluster compared to the base cluster (the very low customer lifetime value cluster), increasing the probability of inclusion in this group by 3.92%.

The importance of accepting social responsibility positively impacts the likelihood of being placed in the clusters of individuals with high, medium, and low customer lifetime value compared to the base cluster. Specifically, the likelihood increases by 1.77% for the first cluster (high customer lifetime value) and by 1.56% for the second cluster (medium customer lifetime value), while it decreases by 0.41% for the fourth cluster (low customer lifetime value). Adherence to ethical norms significantly reduces the likelihood of being placed in the very high and high customer lifetime value clusters relative to the base cluster, while increasing the likelihood of being classified in the low customer lifetime value cluster. Specifically, it reduces the probability of inclusion in the high customer lifetime value cluster by 0.42% compared to the base cluster and increases the likelihood of being in the low customer lifetime value cluster by 2.10% compared to the base cluster.

Table 15- Estimation results of multinomial logit model (Yogurt)

Category	Variable Name	Coefficient	Standard deviation	P-Value	Relative Risk Ratio
Cluster1 People with a very high level of loyalty	Adherence of the brand to the rules of its field of activity	-0.152	0.165	0.356	0.858
	Respect for ethical norms by the brand	-0.315	0.199	0.114	0.729
	Preferably a brand with social responsibility	0.321	0.187	0.001	1.77
Cluster 2 People with a high level of loyalty	Adherence of the brand to the rules of its field of activity	1.367	0.305	0.00	3.925
	Respect for ethical norms by the brand	-0.845	0.296	0.004	0.429
	Preferably a brand with social responsibility	0.45	0.174	0.01	1.569
Cluster 3 People with an average level of loyalty	Adherence of the brand to the rules of its field of activity	-0.134	0.149	0.366	0.873
	Respect for ethical norms by the brand	-0.008	0.174	0.961	0.991
	Preferably a brand with social responsibility	-0.019	0.282	0.066	0.981
Cluster 4 People with low level of loyalty	Adherence of the brand to the rules of its field of activity	-0.132	0.166	0.427	0.875
	Respect for ethical norms by the brand	0.742	0.221	0.001	2.102
	Preferably a brand with social responsibility	-0.886	0.177	0.00	0.412

Researcher's Calculations

Product: Ayran (Yogurt Drink)

In this study, the fourth cluster of the dependent variable, representing individuals with low customer lifetime value, was designated as the base group for the ayran product customer segment. To ensure the optimal and accurate classification of the dependent variable groups, the Wald test was conducted, and the results are presented in Table 16. The statistical values for the pairwise comparisons among the clusters were not all found to be significant. As a result, the first cluster was merged with the second cluster, and upon re-testing, all statistical values became significant. Consequently, the null hypothesis of combining the groups was rejected, confirming that the model, with the four distinct levels of the dependent variable, is appropriate**.**

Table 16- Parent test results for combining loyalty levels (Ayran)

Cluster	Wald Test	
	Stat	Probe
Very high and high loyalty people with medium loyalty people	16.687	0.001
People with very high loyalty and high loyalty with people with low loyalty	10.969	0.012
People with very high and high loyalty with people with very low loyalty	9.498	0.023
People with moderate loyalty versus people with low loyalty	20.405	0.00
People with moderate loyalty and people with very low loyalty	54.573	0.00
People with low loyalty versus people with very low loyalty	54.274	0.00

Researcher's Calculations

The results of the Hausman test are presented in Table 17. According to the table, the statistical values for all groups are found to be statistically insignificant, meaning the null hypothesis of the independence of irrelevant alternatives is not rejected. Therefore, it can be concluded that the groups are independent, and the use of the multinomial logit model for this analysis is appropriate and will not present any issues.

Table 17- The results of the generalized Hausman test for the assumption of independence of unrelated options (IIA)(Ayran)

Cluster	Stat	Probe
People with very high and high loyalty	-5.406	1.00
People with average loyalty	-2.213	1.00
People with low loyalty	2.061	0.865
People with very low loyalty	1.788	0.987

Researcher's Calculations

The goodness of fit for the regression model is reported in Table 18, where the likelihood ratio of the estimated model is 113.83. Given the significance level of less than 1%, this result is statistically significant. Therefore, the regression model is considered significant overall.

Table 18- Good fit criteria of the multinomial logit model (Ayran)

Statistics	Statistics value	Statistics	Statistics value
LR	-466.650	Pseudo R2	0.108
LR-prob	0	Cragg & Uhler's R2	0.192
LR(9)	113.837	AIC	965.3
McFadden's Adj R2	0.078	BIC	-54.776

Researcher's Calculations

Table 19- Estimation results of multinomial logit model (Ayran)

Category	Variable Name	Coefficient	Standard deviation	P-Value	Relative Risk Ratio
Cluster 1 (People with a very high & high level of loyalty)	Adherence of the brand to the rules of its field of activity	-0.422	0.561	0.452	1.525
	Respect for ethical norms by the brand	0.698	0.668	0.296	2.011
	Preferably a brand with social responsibility	0.705	0.517	0.65	2.024
Cluster 2 (People with an average level of loyalty)	Adherence of the brand to the rules of its field of activity	1.297	0.303	0.00	3.661
	Respect for ethical norms by the brand	-0.990	0.283	0.00	0.371
	Preferably a brand with social responsibility	-0.284	0.271	0.295	0.752
Cluster 3 (People with a very low level of loyalty)	Adherence of the brand to the rules of its field of activity	-1.01	0.172	0.00	0.36
	Respect for ethical norms by the brand	0.489	0.193	0.012	1.63
	Preferably a brand with social responsibility	-0.65	0.182	0.00	0.508

Researcher's Calculations

The results of estimating the multinomial logit model using the maximum likelihood method to examine the impact of the specified explanatory variables on customer loyalty for the ayran product are presented in Table 19. The importance of accepting social responsibility has a significant positive impact on the likelihood of being classified in the very low customer lifetime value cluster compared to the base cluster (low customer lifetime value), increasing the probability of inclusion in this group by 2.22%. Additionally, it has a significant negative effect on the likelihood of being placed in the fifth cluster, reducing the probability of inclusion in this cluster by 0.50%.

Adherence to ethical norms negatively impacts the likelihood of being classified in the medium customer lifetime value cluster, while positively influencing the likelihood of being categorized in the very low customer lifetime value cluster compared to the base cluster. Specifically, it decreases the probability of inclusion in the medium customer lifetime value cluster by 0.37% and increases the probability of inclusion in the very low

customer lifetime value cluster by 1.63%.

Individuals who prioritize compliance with industry regulations have a significant positive effect on the likelihood of being placed in the third cluster compared to the base cluster, increasing the likelihood of being in this group by 3.66%. Furthermore, the significance of this factor has a notable negative impact on the likelihood of being classified in the very low customer lifetime value cluster compared to the base cluster, decreasing the probability of inclusion in this group by 0.36%.

Recommendations

Based on the results obtained from 710 completed questionnaires from dairy product consumers in Tehran, customers were segmented into five clusters after standardizing the RFM model parameters and calculating the Dunn statistic. Using the Analytical Hierarchy Process (AHP) method and expert opinions in the field, the weights of the parameters were determined, revealing that the amount of money spent per purchase holds the highest significance among the parameters. Subsequently, Customer Lifetime Value (CLV) was calculated using customer data and the weights derived from the WRFM model, and clusters were ranked based on the computed CLV scores. The highest frequency percentages were found in clusters with low CLV for milk, very low CLV for yogurt, and medium CLV for cheese.

It is important to note that this survey focused on corporate dairy products and reputable brands in the dairy industry, excluding consumers of traditional dairy products. One possible reason for the frequency of low-CLV clusters could be the exclusion of traditional dairy product purchases from the sample. Respondents indicated that they purchase traditional dairy products for some family members while preferring industrial dairy products for others.

To assess the impact of ethical components on CLV and customer segmentation, a multinomial logistic regression model was employed. The findings for each component are detailed below:

- Compliance with Industry Regulations: This factor was not statistically significant for any of the examined products (milk, cheese, yogurt, and Ayran) in any cluster. However, significant results indicate that in higher-CLV clusters, compliance with industry regulations has a strong positive impact, increasing the likelihood of placement in these clusters compared to the base cluster. Conversely, in lower-CLV clusters, compliance with industry regulations has a significant negative effect, reducing the probability of placement in these clusters, as shown by the Relative Risk Ratio (RRR) statistic.
- Respect for Ethical Norms: This factor was also not statistically significant for any of the products across the clusters. However, in contrast to compliance with industry regulations, respect for ethical norms had a significant positive impact on placement in low-CLV clusters, increasing the probability of customers falling into these segments. Conversely, for high-CLV clusters, this factor had a negative effect, reducing the likelihood of placement in these clusters compared to the base group. Customers in low-CLV categories value this component, which may ultimately facilitate their transition into higher-CLV categories.
- Social Responsibility of the Brand: Similar to compliance with industry regulations, this factor had a strong positive impact on high-CLV clusters, increasing the probability of customers being categorized in these segments. Conversely, in low-CLV clusters, this factor showed a significant negative effect, reducing the likelihood of placement in these clusters, as indicated by the RRR statistic.

Product-Specific Findings

Based on the final calculated effects and the estimated logistic regression models, the impact of ethical components on different dairy products is as follows:

- Ayran: Compliance with industry regulations and social responsibility both

increase the likelihood of placement in a higher-CLV cluster, whereas respect for ethical norms is associated with placement in lower-CLV clusters.

- Cheese: The order of influence is as follows: social responsibility, respect for ethical norms, and compliance with industry regulations. Emphasizing ethical norms increases placement in lower-CLV clusters.
- Yogurt: The order of influence is: compliance with industry regulations, respect for ethical norms, and social responsibility. As observed with other products, prioritizing ethical norms results in placement in lower-CLV clusters.
- Milk: The impact of ethical components differs from that of other dairy products. In this case, prioritizing compliance with industry regulations leads to placement in lower-CLV clusters, while social responsibility is associated with placement in higher-CLV clusters.

Managerial Implications

Dairy industry stakeholders can enhance customer loyalty and facilitate transitions to higher-CLV clusters by demonstrating commitment to industry regulations and social responsibility. If brands take proactive measures to respect ethical norms, some consumers of cheese, yogurt, and Ayran may respond positively and shift towards higher-value customer segments. This is particularly crucial given that a significant proportion of consumers for these products currently belong to low-CLV clusters.

The findings suggest that loyal, high-CLV customers in the dairy industry place considerable importance on social responsibility and compliance with industry regulations as ethical factors. As highlighted at the beginning of this study, in today's competitive market, companies must consider factors that influence consumer decisions, interests, and beliefs to foster brand loyalty. Ethical considerations have emerged as a critical domain, with research and logistic model results confirming that in recent years, ethical concerns have significantly impacted purchasing behaviors and consumer perceptions of products and brands.

Correcting negative brand perceptions through marketing efforts is a time-intensive and costly process. Therefore, it is imperative to address these concerns proactively and implement the necessary measures to align brand strategies with ethical consumer expectations.

Recommendations for Future Research

It is recommended that dairy brands conduct comprehensive CLV analyses to assess the potential for increasing customer value and subsequently develop targeted marketing strategies for each customer segment based on their CLV.

For future studies, it is suggested that CLV calculations be conducted separately for each brand. Additionally, a second phase of research could focus on identifying the factors influencing CLV growth for each product within each brand. This approach would provide deeper insights into the strategies employed by various brands to enhance customer lifetime value.

References

1. Abens, R., & Parcheta, D. (2016). Customer Lifetime Value in the Packaged Goods Industry. In *Accountable Marketing* (pp. 83-95). Routledge.
2. Adams, R.J. (2002). Retail profitability and sweatshops: a global dilemma. *Journal of Retailing and Consumer Services*, *9*(3), 147-153. https://doi.org/10.1016/S0969-6989(01)00014-5
3. Akhondzadeh-Noughabi, L., Albadvi, A., & Aghdasi, M. (2014). Mining customer dynamics in designing customer segmentation using data mining techniques. *Journal of Information Technology Management*, *6*(1), 1-30. (In Persian). https://doi.org/10.22059/JITM.2014.50048.
4. Baeva, D.Y. (2011). Strong brands: how brand strategy and brand communication contribute to build brand equity: the case of navigator (Doctoral dissertation).

5. Bargh, J.A. (1994). The four horsemen of automaticity: Intention, awareness, efficiency, and control as separate issues.
6. Bastos, W., & Levy, S.J. (2012). A history of the concept of branding: practice and theory. *Journal of Historical Research in Marketing.*
7. Ben-Akiva, M.E., & Lerman, S.R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.
8. Bivarani, H., & Azimi, M. (2014). Classification of Sadaret Bank customers based on customer value using decision tree. *Productivity Management, 9*(33), 116-135. (In Persian)
9. Blocker, C.P., & Flint, D.J. (2007). Customer segments as moving targets: Integrating customer value dynamism into segment instability logic. *Industrial Marketing Management, 36*(6), 810–822.
10. Buttle, F., & Maklan, S. (2019). *Customer relationship management: concepts and technologies*. Routledge. https://doi.org/10.4324/9781351016551
11. Crane, A., Matten, D., Glozer, S., & Spence, L.J. (2019). *Business ethics: Managing corporate citizenship and sustainability in the age of globalization*. Oxford University Press, USA.
12. Chang, C.H. (2011). The influence of corporate environmental ethics on competitive advantage: The mediation role of green innovation. *Journal of Business Ethics, 104*, 361-370. https://doi.org/10.1007/s10551-011-0914-x
13. Chang, H.C., & Tsai, H.P. (2011). Group RFM analysis as a novel framework to discover better customer consumption behavior. *Expert Systems with Applications, 38*(12), 14499-14513. https://doi.org/10.1016/j.eswa.2011.05.034
14. Cooksley, G. (2007). Customer lifetime value models: do they predict actual behaviour?
15. Dickson, P.R., & Ginter, J.L. (1987). Market segmentation, product differentiation, and marketing strategy. *Journal of Marketing, 51*(2), 1-10.
16. Dunn, J.C. (1974). Well-separated clusters and optimal fuzzy partitions. *Journal of Cybernetics, 4*(1), 95-104.
17. Estrella-Ramon, A.M., Sanchez-Perez, M., Swinnen, G., & VanHoof, K. (2013). A marketing view of the customer value: Customer lifetime value and customer equity. *South African Journal of Business Management, 44*(4), 47-64. https://hdl.handle.net/10520/EJC146688
18. Fader, P.S. (2012). *Customer centricity: Focus on the right customers for strategic advantage*. Wharton Digital Press.
19. Feiz, S., Ghotbabadi, A.R., & Khalifah, Z.B. (2016). Customer Lifetime Value in organizations. *Asian Journal of Research in Social Sciences and Humanities, 6*(5), 53-58.
20. Ghale, R.D., Karimi, F., & Dinani, H.G. (2021). Identifying and prioritizing dimensions and indicators of customer lifetime value for supplemental health insurance industry. *Jundishapur Journal of Health Sciences, 13*(4).
21. Glady, N., Baesens, B., & Croux, C. (2009). A modified Pareto/NBD approach for predicting customer lifetime value. *Expert Systems with Applications, 36*(2), 2062-2071.
22. Gleim, M.R., Smith, J.S., Andrews, D., & Cronin Jr, J.J. (2013). Against the green: A multi-method examination of the barriers to green consumption. *Journal of Retailing, 89*(1), 44-61. https://doi.org/10.1016/j.jretai.2012.10.001
23. Green, W. (2011), *Econometric Analysis*, Prentice Hall.
24. Greene, J., & Haidt, J. (2002). How (and where) does moral judgment work?. *Trends in Cognitive Sciences, 6*(12), 517-523.
25. Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., Ravishanker, N., & Sriram, S. (2006). Modeling customer lifetime value. *Journal of Service Research, 9*(2), 139-155. https://doi.org/10.1177/1094670506293810
26. Haenlein, M. (2017). How to date your clients in the 21st century: Challenges in managing customer relationships in today's world. *Business Horizons, 60*(5), 577-586.

https://doi.org/10.1016/j.bushor.2017.06.002
27. Haidt, J. (2007). The new synthesis in moral psychology. *Science*, *316*(5827), 998-1002. https://doi.org/10.1126/science.1137651
28. He, X., & Li, C. (2016, December). The research and application of customer segmentation on e-commerce websites. In 2016 6th International Conference on Digital Home (ICDH) (pp. 203-208). IEEE
29. Hausman, J., & McFadden, D. (1984). Specification tests for the multinomial logit model. *Econometrica: Journal of the Econometric Society*, 1219-1240. https://doi.org/10.2307/1910997
30. Isengildina, O., & Hudson, D. (2001). Factors affecting hedging decisions using evidence from the cotton industry. 10.22004/ag.econ.18970
31. Jasek, P., Vrana, L., Sperkova, L., Smutny, Z., & Kobulsky, M. (2018). Modeling and application of customer lifetime value in online retail. In *Informatics*, *5*(1), 2. MDPI. https://doi.org/10.3390/informatics5010002
32. Jasek, P., Vrana, L., Sperkova, L., Smutny, Z., & Kobulsky, M. (2019). Comparative analysis of selected probabilistic customer lifetime value models in online shopping. *Journal of Business Economics and Management*, *20*(3), 398-423. https://doi.org/10.3846/jbem.2019.9597
33. Jamali, S., & Navaei, Y.D. (2016). A two-level product recommender for E-commerce sites by using sequential pattern analysis. *International Journal of Integrated Engineering*, *8*(1).
34. Jandaghi, G., Ghoreishi, S.M., & Ahadi Shoar, S.M. (2017). Investigating the dimensions of social capital and its relation to moral marketing (Case: Sepah Bank Branches of Qom Province). *Social Capital Management*, *4*(3), 309-332. (In Persian). https://doi.org/10.22059/jscm.2018.136506. 1133
35. Jiang, X., Bai, R., Wallace, S.W., Kendall, G., & Landa-Silva, D. (2021). Soft clustering-based scenario bundling for a progressive hedging heuristic in stochastic service network design. *Computers & Operations Research*, *128*, 105182.
36. Jones, D.B., & Tadajewski, M. (Eds.). (2016). The Routledge companion to marketing history. Routledge.
37. Kasprova, A. (2020). Customer Lifetime Value for Retail Based on Transactional and Loyalty Card Data.
38. Khanleri, A., & Gorohi, B. (2012). Categorizing and estimating the value of bank customers through customer lifetime value and possible patterns. The 4th International Conference on Marketing of Banking Services, Tehran, Center for International Broadcasting Conferences. (In Persian)
39. Kim, S-Y., Jung, T.-S., Suh, E.-H., & Hwang, H.-S. (2006). Customer segmentation and strategy development based on customer lifetime value: A case study. *Expert Systems with Applications*, *31*(1), 101-107.
40. Kumar, V., Pozza, I.D., Petersen, J.A., & Denish Shah, D. (2009). Reversing the logic: The path to profit¬ability through relationship marketing. *Journal of Interactive Marketing*, *23*(2), 147-156. https://doi.org/10.1016/j.intmar.2009.02.003
41. Lavorata, L. (2014). Influence of retailers' commitment to sustainable development on store image, consumer loyalty and consumer boycotts: Proposal for a model using the theory of planned behavior. *Journal of Retailing and Consumer Services*, *21*(6), 1021-1027. https://doi.org/10.1016/j.jretconser.2014.01.003
42. Scott Long, J. (1997). Regression models for categorical and limited dependent variables. *Advanced Quantitative Techniques in the Social Sciences*, *7*.
43. Modesto, J.C.P. (2020). Marketing Communication Plan-TREE Real Estate Experience (Doctoral dissertation, ISCTE-Instituto Universitario de Lisboa (Portugal)).
44. Monalisa, S. (2018). Klasterisasi Customer Lifetime value dengan Model LRFM Menggunakan

Algoritma K-Means. *Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK)*, *5*(2), 247-252. https://doi.org/10.25126/jtiik.201852690

45. Monalisa, S., Nadya, P., & Novita, R. (2019). Analysis for customer lifetime value categorization with RFM model. *Procedia Computer Science*, *161*, 834-840. https://doi.org/10.1016/j.procs. 2019.11.190
46. Moll, J., De Oliveira-Souza, R., Bramati, I.E., & Grafman, J. (2002). Functional networks in emotional moral and nonmoral social judgments. *Neuroimage*, *16*(3), 696-703. https://doi.org/10. 1523/JNEUROSCI.22-07-02730.2002
47. Moll, J., Zahn, R., De Oliveira-Souza, R., Krueger, F., & Grafman, J. (2005). The neural basis of human moral cognition. *Nature Reviews Neuroscience*, *6*(10), 799-809. https://doi.org/10. 1038/nrn1768
48. Mosaddegh, A., Albadvi, A., Sepehri, M.M., & Teimourpour, B. (2021). Dynamics of customer segments: A predictor of customer lifetime value. *Expert Systems with Applications*, *172*, 114606. https://doi.org/10.1016/j.eswa.2021.114606
49. Mothersbaugh, D.L., Hawkins, D.I., Kleiser, S.B., Mothersbaugh, L.L., & Watson, C.F. (2020). Consumer behavior: Building marketing strategy. New York, NY, USA: McGraw-Hill Education. 1-260-10004-9
50. Niazian, A. (2018). *Examining the moderating role of ethical marketing in the relationship between knowledge sharing and employee-oriented innovation (case study: public hospitals of Ilam province)* [Master's thesis, Bakhtar Institute of Higher Education, Ilam]. (In Persian)
51. Pecoraro, M.G., & Uusitalo, O. (2014). Conflicting values of ethical consumption in diverse worlds–A cultural approach. *Journal of Consumer Culture*, *14*(1), 45-65. https://doi.org/10.1177/ 1469540513485273
52. Rana, J., & Paul, J. (2017). Consumer behavior and purchase intention for organic food: A review and research agenda. *Journal of Retailing and Consumer Services*, *38*, 157-165. https://doi.org/10.1016/j.jretconser.2017.06.004
53. Shaw, D., McMaster, R., & Newholm, T. (2016). Care and commitment in ethical consumption: An exploration of the 'attitude–behaviour gap'. *Journal of Business Ethics*, *136*, 251-265. https://doi.org/10.1007/s10551-014-2442-y
54. Shiri, A., Dehghani Soltani, M., Soltani Banavandi, A., & Azadi, Y. (2017). The effect of service-orientation on customer's loyalty with mediating role of service quality in hotel industry (A case study: Kerman's Pars Hotel). *Journal of Tourism and Development*, *6*(2), 39-62. (In Persian). https://doi.org/10.22034/jtd.2020.110396
55. Tsarenko, Y., Ferraro, C., Sands, S., & McLeod, C. (2013). Environmentally conscious consumption: The role of retailers and peers as external influences. *Journal of Retailing and Consumer Services*, *20*(3), 302-310. https://doi.org/10.1016/j.jretconser.2013.01.006
56. Winer, R.S. (2001). Customer relationship management: a framework, research directions, and the future. *Haas School of Business*.
57. Willer, H., & Lernoud, J. (2016). The world of organic agriculture. Statistics and Emerging Trends 2016. Research Institute of Organic Agriculture FiBL and IFOAM Organics International (Accessed 23 October 2017). http://orgprints.org/31151/1/willer-lernoud-2016-world-of-organic.pdf
58. Yeh, I.C., Yang, K.J., & Ting, T.M. (2009). Knowledge discovery on RFM model using Bernoulli sequence. *Expert Systems with Applications*, *36*(3), 5866-5871. https://doi.org/10.1016/j.eswa. 2008.07.018
59. Yoseph, F., Ahamed Hassain Malim, N.H., Heikkilä, M., Brezulianu, A., Geman, O., & Paskhal Rostam, N.A. (2020). The impact of big data market segmentation using data mining and clustering techniques. *Journal of Intelligent & Fuzzy Systems*, *38*(5), 6159-6173. https://doi.org/10.3233/JIFS -179698

60. Zehir, C., & Narcıkara, E. (2016). E-service quality and e-recovery service quality: Effects on value perceptions and loyalty intentions. *Procedia-Social and Behavioral Sciences*, *229*, 427-443. https://doi.org/10.1016/j.sbspro.2016.07.153

Journal of Agricultural Economics & Development

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مقاله پژوهشی

جلد ۳۸، شماره ۴، زمستان، ۱۴۰۳، ص. ۳۷۱-۳۹۱

بررسی مؤلفه‌های اخلاقی مؤثر بر ارزش دوره عمر مشتری محصولات لبنی در شهر تهران

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تاریخ دریافت: ۱۴۰۳/۰۵/۲۷

تاریخ پذیرش: ۱۴۰۳/۰۷/۲۸

چکیده

امروزه نگهداری و تقویت وفاداری مشتری در راستای محصولات یا خدمات یک شرکت، عموماً نکته اصلی و مرکزی فعالیت‌های بازاریابی شده است. ازجمله مواردی که می‌تواند بر بهبود وفاداری مشتریان به برند/ محصول تأثیرگذار باشد، بازاریابی اخلاقی است. بازاریابی اخلاقی حوزه‌ای از اخلاق کاربردی است که با اصول اخلاقی پنهان در رفتار، تبلیغ و تنظیم در بازاریابی ارتباط دارد. مصرف‌گرایی اخلاقی نیز در دو دهه اخیر به دلیل مسائل اجتماعی و زیست‌محیطی اهمیت پیدا کرده است. در این راستا در این مطالعه به هدف بررسی مؤلفه‌های اخلاقی بر ارزش دوره عمر مشتری برای مصرف‌کنندگان محصولات لبنی در تهران در سال ۱۴۰۲ انجام شده است. برای دستیابی به هدف، ۷۱۰ پرسشنامه در شهر تهران تکمیل گردید و با استخراج اطلاعات مورد نیاز برای محاسبه دوره عمر مشتری از روش GWRFM استفاده گردید و نتایج نشان‌دهنده درصد فراوانی بالای خوشه‌های با ارزش دوره عمر پایین بودند. در مرحله دوم با استفاده از لاجیت چندگانه به بررسی تأثیر مؤلفه‌های اخلاقی بر CLV پراخته شد که نتیجه حاکی از اهمیت پایبندی به قوانین حوزه فعالیت و پذیرش مسئولیت اجتماعی بر ارزش دوره عمر مشتری بصورت مثبت و معنی‌دار بود. از این رو پیشنهاد می‌شود فعالان صنعت لبنیات با مطمئن کردن مشتریان از پایبندی به قوانین حوزه فعالیت این صنعت و همچنین پذیرش مسئولیت اجتماعی می‌توانند آنها را به خوشه‌های بالاتر منتقل کرده و جزو مشتریان وفادار خود قرار دهند. اگر در زمینه احترام به هنجارهای اخلاقی نیز اقدامات مثبتی انجام گردد بخش قابل توجهی از مصرف‌کنندگان محصولات پنیر، ماست و دوغ را تحت تأثیر قرار می‌دهد و سبب حرکت آن‌ها به سوی قرارگیری در زمره مشتریان باارزش این صنعت می‌شود.

واژه‌های کلیدی: ارزش دوره عمر مشتری، بازاریابی اخلاقی، مصرف‌گرایی اخلاقی، GWRFM

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https://doi.org/10.22067/jead.2024.89411.1290

Journal of Agricultural Economics & Development

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

Research Article
Vol. 38, No. 4, Winter 2025, p. 393-411

Risk Analysis of Round Fandoghi Pistachio Contracts in the Iran Mercantile Exchange Market

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Received: 07-08-2024
Revised: 14-10-2024
Accepted: 19-10-2024
Available Online: 02-11-2024

How to cite this article:
Sadafi Abkenar, S., Chizari, A.H., Rafiee, H., & Salami, H. (2025). Risk analysis of round Fandoghi pistachio contracts in the Iran mercantile exchange market. *Journal of Agricultural Economics & Development*, *38*(4), 393-411. https://doi.org/10.22067/jead.2024.89445.1289

Abstract

Iran Mercantile Exchange is striving to become a regional hub for price discovery of essential commodities and raw materials, providing producers with financial instruments and risk management tools. This study investigates the optimal hedge ratio in future and commodity deposit receipts (spot) contracts for Round Fandoghi pistachios. Using the BEKK-VAR-TARCH model, the impact of seasonal and daily volatility on returns and hedge ratios was assessed over the period from 19 October 2018 to 18 January 2022. The results showed that volatility on specific days of the week and during different seasons affect speculative and investment decisions in the commodity exchange. Particularly, sharp volatility during certain periods can lead to significant changes in returns and hedge ratios. These findings suggest that investors should update their investment strategies based on seasonal and daily volatilities. Additionally, the importance of utilizing financial instruments suited to market conditions for managing existing risks was confirmed. Ultimately, investors, speculators, and policymakers in the commodity exchange are advised to pay special attention to temporal changes and existing volatilities when composing their investment portfolios and adjusting hedge strategies. Furthermore, the use of futures contracts and derivative instruments is recommended as risk management approaches. This study contributes to a better understanding of volatility behavior and offers strategies for improved risk management in the Round Fandoghi pistachio market.

Keywords: Optimal commodity portfolio, Optimal hedge ratio, Seasonal data behavior

https://doi.org/10.22067/jead.2024.89445.1289

Introduction

The primary priority of Iran Mercantile Exchange (IME) is focus on becoming a regional price reference for essential commodities and intermediary raw materials (Iran Mercantile Exchange, 2024). IME serves as a principal venue for hedging price volatility risks. Risk hedging enables a production unit to control the costs of the raw materials needed for manufacturing. A hedge is an investment aimed at reducing the risk posed by unfavorable price changes of an asset (Geman, 2005). Typically, hedging encompasses taking a compensatory or reverse position against the guaranteed position. By utilizing this strategy, a producer can more effectively manage product pricing (Geman, 2005). Common hedging techniques involve taking a compensatory position in derivatives contracts associated with the current position. Another form of hedging can occur through diversification. The need for hedging arises when a producer lacks control over the pricing of raw materials or finished products. The capacity to decide on the level of risk one is willing to accept or transfer via commodity exchanges is known as comprehensive risk tolerance (Iran Mercantile Exchange, 2024). In essence, hedging incurs costs, and a complete hedge eliminates all risks in a position or investment portfolio (Geman, 2005).

Hedging risks in agricultural products through the creation of a diversified portfolio has received limited promotion and attention. IME offers various hedging instruments. The exchange uses futures contracts and commodity deposits (spot contracts) to manage price volatility. Futures contracts and Commodity Deposit Receipts (CDRs) are two essential financial instruments in commodity and derivative markets, designed to manage risk and facilitate investment. A futures contract is a legally binding agreement between a buyer and a seller to trade a commodity at a predetermined price on a specified future date. These contracts are particularly useful for managing price risks, benefiting farmers, investors, and other market participants. Settlement and delivery of the commodity take place upon the contract's expiration. Conversely, a commodity deposit certificate represents ownership of goods stored in approved warehouses, and these receipts are traded on the IME. Commodity deposit receipts allow for immediate settlement without requiring physical delivery, with prices determined by the commodity's current market value, making them an efficient tool for spot transactions. Due to their instant settlement, market-based pricing, and ability to transfer ownership without physical delivery, commodity deposit receipts can serve as effective proxies for spot market transactions. They facilitate fast settlement and ownership transfer based on actual market conditions, reducing the risks associated with storage and delivery. This feature positions commodity deposit receipts as a viable alternative to spot market trading and plays a key role in optimizing inventory management and investment in physical goods (Iran Mercantile Exchange, 2024).

Pistachio is one of the two main agricultural products traded on the IME; however, during October 19, 2018, to January 18, 2022, the traded value of this product declined from approximately 865 billion Rials to around 19 billion Rials, while the trading volume dropped from about 984 tons to just 3.4 tons (Iran Mercantile Exchange, 2024). In 2008 and 2009, 100 tons of pistachios produced by Sirjan Agricultural Company were offered. However, in 2016, about 30 tons of pistachios were traded, and during the same year, Kashiri Kolaei & Hosseini Yekani (2016) showed that despite no change in overall pistachio exports, demand for pistachios would increase in Khorasan Razavi, Yazd, and Semnan provinces of Iran, while provinces such as Fars, Qom, and Qazvin would lose market share. During the review period, only Round Fandoghi pistachios were traded on the IME, though other varieties such as Akbari pistachios saw minimal trade (Iran Mercantile Exchange, 2024). It is also noteworthy that due to frost damage in Kerman in 2021, round pistachio production significantly declined (Pakdaman *et al.*, 2023), though it is likely that pistachios will return to the IME within a year once orchards recover

from frost damage (Tajabadipour & Afarasteh, 2022). On the other hand, considering the large number of pistachio producers and the generally competitive production conditions, producers wish to see pistachio trading remain active on the IME to facilitate price discovery. However, in terms of exports, where the market is near-monopolistic, this preference does not exist. Given that pistachio is one of the most important agricultural products in Iran, the findings of this study could be used to inform future transactions for re-entering Round Fandoghi pistachios to the IME.

Various studies have shown that price volatility and hedge effectiveness vary across agricultural and energy commodity markets. GARCH, ARIMA, and neural networks have been widely used for price analysis and forecasting, with factors such as wholesale prices, risk-free interest rates, and government policies having significant impacts. Additionally, combining futures contracts with insurance and using hedge indices like BDI and CRBI can improve hedge efficiency. Moreover, the relationship between crude oil and agricultural commodity prices turned positive after 2006, with market liquidity reductions leading to collective price shocks. However, there is still a gap in the knowledge regarding risk analysis of the pistachio commodity in the IME, highlighting the need for further research in this area.

To support IME's objectives of promoting transparency and competition in the market, this study seeks to assess the risks faced by pistachio producers. For this purpose, we examined the risk hedging for Round Fandoghi pistachios using two instruments, i.e. futures contracts and investment deposits, by analyzing daily data from October 19, 2018, to January 18, 2022.This investigation answered the question of how the optimal portfolio between the two contracts has evolved throughout the study period.

Literature Review

Extensive studies have been conducted on the risk and price volatility of agricultural products in the commodity exchanges of Iran and the world. This section reviews several recent studies over the past decade.

Kavoosi Kalashami & Kavoosi Kalashami (2017) utilized the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to analyze the price variance of rice in wholesale and retail markets from April 1999 to March 2014. Their results indicated a positive effect of wholesale rice prices on price variance fluctuations. Baghestani *et al.* (2016) analyzed and forecasted monthly and weekly data for soybean meal from October 2004 to March 2013 using the Group Method of Data Handling (GMDH) neural network and Autoregressive Integrated Moving Average (ARIMA). They found that the GMDH method provided superior results. Ghazali *et al.* (2016) conducted a comparison of agricultural products with other commodities traded on the Iran Mercantile Exchange (IME) by collecting questionnaires from 145 commodity trading experts and estimating structural equations. Their findings revealed that three major factors—governmental (weak incentive and tax policies) and structural (product standardization issues and perishability)—lead to the failure of agricultural products in the IME.

Mohammadi *et al.* (2016) compared the barley market using daily data from October 2007 to October 2011 with the Vector Autoregressive (VAR) and GARCH models. Their results showed that the price volatility of barley in the IME was higher than in the Chicago Mercantile Exchange (CME), indicating the relatively lower efficiency of the IME. Ahangari *et al.* (2017) employed numerical taxonomy and weighted taxonomy methods for 10 agricultural products in 2013 to rank the products that could be traded in the IME. Their results highlighted those factors like importance coefficient and continuity of supply are critical success factors. Based on their findings, rice, corn, wheat, and tea were identified as the most important agricultural products for trading in the IME. However, by the time of writing this article, only pistachios and saffron remained traded in the IME, with pistachio trading in decline. Pishbahar *et al.*

(2018) analyzed weekly soybean meal and corn grain prices from April 2013 to August 2016 for Asian option contracts using the Binomial Tree Method. Their results showed that increases in asset prices, price volatility, and risk-free interest rates led to higher call option prices. Conversely, a shorter time to maturity reduced the value of the option.

Amjadi *et al*. (2017) calculated hedge ratios and hedge effectiveness for corn, soybean, wheat, and cotton in the Wall Street commodity exchange using monthly data from 2014. They demonstrated that corn price risk decreased by 26%, and soybeans had 88% higher hedge efficiency compared to corn. Borzabadi Farahani *et al*. (2021) estimated the optimal static hedge ratio of the gold coin market against saffron futures contracts using daily data from June 2018 to October 2019 with copula functions and wavelet decomposition. Their results indicated the ability of saffron futures contracts to hedge gold coin spot contracts in the medium and long term. Miremadi et al. (2021) examined the efficiency of saffron futures contracts daily from December 2018 to December 2019 using the Vector Error Correction Model (VECM). Their findings showed a short- and long-term relationship between futures prices to spot prices.

Haj Seyed Javadi & Heydari (2022) forecasted daily data for saffron futures contracts from May 2019 to May 2020 in the IME using a hybrid model comprising nonlinear genetic algorithms, deep neural networks, random forests, support vector machines, and Monte Carlo simulations. Li (2012) used the Generalized Dynamic Conditional Correlation (GDCC) model, Time-Varying Transition Probabilities (TVTP), and the Markov Regime-Switching VECM (MRS-VECM) to obtain the optimal hedge ratio for natural gas futures and spot contracts from November 1994 to June 2009. Li (2012) concluded that varying the hedge ratio based on variance produced better results than a fixed ratio for strategic hedge planning. Alausa (2014), in his doctoral dissertation, used weekly data from 1977 to December 26, 2012, for wheat, corn, crude oil, heating oil, gold, silver, S&P500, and British and Canadian currencies. He employed Markov Switching VECM-MSM, Conditional and Unconditional Value-at-Risk (VaR), and ARX-MSM models to analyze extreme co-movements in commodity prices. His findings indicated that extreme price co-movements are more prevalent during volatile periods.

Moumouni (2016) estimated Monte Carlo Markov Chains and equilibrium modeling using monthly data from January 1990 to August 2015 for eight agricultural products. His results showed that static hedge strategies for rotating processes increased the risks of splitting risk between near and far futures contracts and inter-commodity hedging. He proposed that combining futures contracts with insurance would enhance hedge efficiency. Zhang & Chuan (2006) studied simultaneous price movements of oil, silver, gold, corn, and live cattle from January 2005 to December 2013 using co-integration analysis and the Granger causality test. They found that when market liquidity decreases, prices of these commodities decline collectively, leading to price shocks and increased inflation volatility. Yahya *et al.* (2019) examined temporal and frequency correlations between agricultural products and crude oil from July 1986 to June 2016 using wavelet transformation. Their method, which included the Maximum Overlap Discrete Wavelet Transform (MODWT), DCC-Student-t copula, and ARMA-EGARCH, demonstrated correlations between variables and facilitated long-term strategic planning. They also designed investment portfolios and calculated hedge ratios to minimize and manage investment risks.

Zhao *et al*. (2019) estimated the optimal hedge for daily crude oil data from December 2009 to October 2016 using the Fractionally Integrated GARCH–Extreme Value Theory–Copula–VaR (FIGARCH–EVT–Copula–VaR) approach. Their integrated method provided dynamic analysis of indicators such as mean returns, return variance, mean-to-variance ratio, and hedge efficiency. Shen (2020) studied the risk effects of COVID-19 on agricultural

product prices in 2020. He analyzed weekly data from 2010 to 2020 for corn, soybean, wheat, and live cattle futures contracts using the BEKK-MGARCH model. Shen's findings showed a positive relationship between past variance and current price changes for index traders of corn and live cattle. Han *et al*. (2020) explored the variance correlation between energy (oil and gas) and agricultural products (corn, soybean, and wheat), the US Dollar Index (USDX), the Baltic Dry Index (BDI), and the Commodity Research Bureau Index (CRBI) from January 1995 to March 2017 using the VARMA-BEKK-MGARCH model. Their results indicated that the BDI, CRBI, and USDX are suitable hedge indicators under extreme conditions. Singhal & Biswal (2021) used the MRS-VAR model to estimate the optimal hedge ratio and determine the dynamic commodity portfolio for agricultural, energy, and metal commodities over the weekly period from January 2005 to December 2013. Their results showed the presence of organizational changes across all assets, indicating their behavioral dependence on economic conditions.

Rezitis *et al*. (2024) combined the Markov Switching model, four-variable VAR, DCC, and BEKK-GARCH models to estimate the impact of macroeconomic shocks (e.g., COVID-19) on energy (oil and gas) and agricultural (corn and soybean) products using daily data from July 1996 to November 2020. Their results showed that energy commodities and shock indicators could be powerful tools for hedging agricultural products. Schneider & Tavin (2024) analyzed seasonal effects on hedge strategies for agricultural products such as corn, cotton, soybean, sugar, and wheat using daily data from 2007 to 2019, gathered from USDA and FAO. Their GARCH and Stochastic Volatility (SV) models demonstrated the significant impact of price volatility on hedging strategies. They emphasized the importance of selecting an appropriate GARCH model to improve hedge ratios and stressed the influence of seasonal price fluctuations on market behavior.

Materials and Methods

To determine an optimal dynamic portfolio strategy for hedging risk related to Round Fandoghi pistachios in the Iran Mercantile Exchange (IME) from the perspective of both suppliers and consumers, the theory of optimal portfolio selection, first introduced by Markowitz (1952), is employed. This theory illustrates portfolio selection as a trade-off between risk and return, with two primary scenarios: (1) maximizing the return or wealth of the trader at an acceptable level of risk, and (2) minimizing risk for a given level of expected return or wealth. For hedging a commodity contract, the optimal hedge ratio (b) is derived between two types of contracts: futures contracts and commodity deposit receipts. Generally, a commodity portfolio consists of multiple commodities, meaning this study seeks to determine the optimal percentage allocation to each of these contracts.

To reduce price risk, the hedger must take futures positions to maximize the reduction of price volatility in the cash market (Edwards & Ma, 1992). If the hedge ratio is not accurately estimated, the likelihood of effective hedging diminishes, as hedgers cannot determine the number of futures contracts needed (Chance, 1989). A precise estimation of the hedge ratio helps investors minimize basis risk and apply appropriate hedging strategies and techniques, such as managing trading risk from financial obligations, operational risk from currency fluctuations, and the risk of foreign currency assets. Hence, estimating the optimal hedge ratio is crucial.

The hedge ratio (h) is derived from the ratio of futures positions (Q_f) to cash positions (Q_c) as per Equation (1):

$$h = \frac{Q_f}{Q_c} \quad (1)$$

Where Q_f is the number of futures contracts required for hedging, and Q_c represents the number of cash contracts whose risk must be hedged, assuming Q_c remains constant. By using the relationship $Q_f = hQ_c$, the number of futures contracts needed for optimal hedging can be calculated (Chen et al., 2003).

There are various methods to estimate the

hedge ratio. Depending on different objective functions, optimal hedge ratios can be determined through different approaches, such as Minimum Variance (MV), Mean-Variance, Maximum Expected Utility, Generalized Gini Mean (MEG), and Generalized Semivariance (GSV). The MV method, proposed by Johnson (1960), aims to reduce portfolio risk by minimizing the variance of the hedged commodity portfolio. However, the MV method has been criticized for neglecting expected return as a factor in the portfolio. The mean-variance strategy was suggested to account for both expected return and risk (variance) in hedging a commodity portfolio. Although this strategy avoids the drawbacks of the MV method, it requires the maximization of expected utility, which in turn necessitates calculating a quadratic utility function with a jointly normal distribution, making this method computationally complex. The MEG and GSV methods are proposed to obtain hedge ratios consistent with the concept of stochastic dominance. MEG is not restricted by specific assumptions regarding probability distributions for utility functions and returns (Chen *et al*., 2003).

Assuming that cash and futures prices do not move in perfect parallel, the simplest way to measure their relationship and construct a properly hedged commodity portfolio is to execute a "linear regression" as shown in Equation (2):

$$P_c = a + bP_f + e \quad (2)$$

Where P_c is the spot price, and P_f is the future price. To minimize the hedger's potential risk, the hedge ratio is estimated through the regression in Equation (2) and calculated using Equation (3):

$$b = \frac{\Delta P_c}{\Delta P_f} \quad (3)$$

The cash price moves in proportion to the futures price by a factor of b. When $b = 1$, the cash price and futures price move exactly in the same direction and magnitude. The net value of the futures positions perfectly offsets changes in the cash market price. This one-to-one scenario is known as "perfect hedging" or "naive hedging," though futures and cash prices may not always fluctuate proportionately. A "perfect hedge" is generally impractical, especially for cross-hedging (Chance, 1989; Siegel & Siegel, 1990).

Regression estimations on price changes $(\Delta P_c, \Delta P_f)$, percentage price changes $(\Delta P_c/P_c\ , \Delta P_f/P_f\ )$, and logarithmic differences $(\log(P_{c,t}/P_{c,t-1}\ ), \log(P_{f,t}/P_{f,t-1}\ ))$ have been proposed in various studies to estimate the optimal hedge ratio. The suitability of price-level regression in financial and commodity markets is a debated topic. Siegel & Siegel (1990) argued that price-level regression only captures hedging motivation and downplays speculative incentives. While statistically, price-level regression indicates a high correlation between futures and cash prices, it does not account for correlations between price changes, violating the assumptions of OLS. Additionally, time-series data often exhibit autocorrelation and heteroscedasticity in error terms, complicating price-level regression. Myers & Thompson (1989) suggested price-level regression is inappropriate, while price change regression provides better estimates for commodities like corn, soybeans, and wheat. Witt *et al.* (1987) defended the price-level model, arguing it is suitable for hedging predictions, and no clear evidence suggests that price change or percentage change regressions are superior. Ultimately, Siegel & Siegel (1990) generalized that percentage price change regression is more appropriate for financial futures contracts, while price change regression suits commodity futures contracts. Many researchers prefer logarithmic difference regression, as it better captures the non-linear relationship between futures and cash prices (Ameur *et al*., 2022; Choudhry, 2009).

This study employs the Mean-Variance (MV) method, where price risk is minimized by reducing the variance of commodity portfolio returns. The return on a hedged commodity portfolio is calculated using Equation (4):

$$r_t = r_{c,t} - \beta_{t-1} r_{f,t} \quad (4)$$

Where β_{t-1} is the hedge ratio, and $r_{c,t}$ and $r_{f,t}$ represent the log-returns of the pistachio certificate market and pistachio futures market

between times t and $t-1$, calculated as $logP_{c,t} - logP_{c,t-1}$ and $logP_{f,t} - logP_{f,t-1}$, respectively.

The expected return and the variance of the hedging effectiveness of the commodity portfolio are calculated in equations (5) and (6), respectively.

$$E(r)_t = E(r_{c,t}) - \beta_{t-1} E(r_{f,t}) \quad (5)$$

$$\text{var}(r_t) = \text{var}(r_{c,t}) + \beta_{t-1}^2 \text{var}(r_{f,t}) - 2\beta_{t-1} \text{cov}(r_{c,t}, r_{f,t}) \quad (6)$$

Where $\text{cov}(r_{c,t}, r_{f,t})$ represents the covariance between the returns of the Round Fandoghi pistachio commodity deposit certificate market and the Round Fandoghi pistachio futures market. In equation (5), assuming $\beta_{t-1} = 0$ and minimizing the variance, equation (7) yields the hedge ratio.

$$\beta_{t-1} = \frac{\text{cov}(r_{c,t}, r_{f,t})}{\text{var}(r_{f,t})} \quad (7)$$

The optimal hedge ratio is dependent on the logarithm of the futures contract return and the correlation between the futures contract and the commodity deposit. This ratio is always less than 1, as the volatility of futures contracts is generally higher than that of commodity deposit contracts (Choudhry, 2003).

The Hylleberg *et al.* (1990) method is utilized for testing seasonal unit roots. This method is one of the key approaches for assessing seasonal unit roots in time series data, particularly suitable for periodic data such as daily, weekly, seasonal, or monthly datasets. In this study, given the daily data that excludes Fridays, the Hylleberg model is defined as a 6-period equation (8):

$$\begin{cases} \Delta_6 y_t = \mu + \pi_0 L(1 + L^1 + L^2 + L^3 + L^4 + L^5) y_t + \Omega + \sum_{i=1}^{p} \phi_i \Delta_6 y_{t-i} + \epsilon_t \\ \mu = \alpha + \beta t + \sum_{j=1}^{5} \gamma_j D_j \\ \Omega = \left[\pi_{1,1} \cos\left(\frac{2\pi}{6}\right) + \pi_{1,2} \sin\left(\frac{2\pi}{6}\right)\right] y_t + \left[\pi_{2,1} \cos\left(\frac{4\pi}{6}\right) + \pi_{2,2} \sin\left(\frac{4\pi}{6}\right)\right] y_t + \left[\pi_{3,1} \cos\left(\frac{6\pi}{6}\right) + \pi_{3,2} \sin\left(\frac{6\pi}{6}\right)\right] y_t \end{cases} \quad (8)$$

Where μ is a linear combination of observable variables such as the intercept (α), trend (t), and seasonal dummy variables (D_j for all $j = 1,2,3,4,5$), and L^k is the k-th lag operator. Additionally, Ω includes variables that indicate seasonal unit root effects at frequencies $2\pi/6$, $4\pi/6$, and $6\pi/6$. The term $\pi_0 L(1 + L^1 + L^2 + L^3 + L^4 + L^5) y_t$ represents the seasonal pattern determined within the data. Essentially, it filters the data by aggregating values at various seasonal lags. The term $\Delta_6 y_t$ denotes the seasonal difference of the 6-period time series, calculated as $(1 - L^6) y_t$. Furthermore, the term $\sum_{i=1}^{p} \phi_i \Delta_6 y_{t-i}$ represents lags of the dependent variable, with the number of lags (p) depending on the white noise condition of the error term (ϵ_t) (Castro *et al.*, 2012). In this study, the selection of the number of autoregressive lags is determined using a "Top-Down" approach; that is, the maximum possible lags for the testing pattern are chosen, which presumably white out the results of the error term, followed by the reduction of lags and reiteration of the test until the results deviate from white noise upon the reduction of lags. Therefore, the optimal lag is the one that exceeds the maximum lack of white noise in the error term by one unit. It is noteworthy that to prevent overfitting risks, the study also considers other criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) as auxiliary metrics to balance model complexity with data fit (Enders, 2014).

Bivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are employed in econometrics for the simultaneous modeling and analysis of the volatility of two-time series. These models are derived from the generalization of univariate GARCH models, capturing the interrelationships between the volatilities of two-time series. Specifically, univariate GARCH models are designed to model the volatility of a single time series such that the volatility of a dependent variable can change over time and is contingent upon its past values. Conversely, in the bivariate GARCH model, this concept is extended to two-time series, encompassing the joint behavior of both series, including their volatilities and correlations. In essence, this model consists of three parameters: conditional variance, conditional covariance, and structural correlation. The application of bivariate GARCH models is

common in financial economics for analyzing asset return co-movements, risk assessment, or modeling the joint behavior of time series (Choudhry, 2009).

Among the models mentioned in the previous section, the bivariate GARCH-VAR and BEKK-VAR models are utilized for analyzing and modeling the volatilities and dynamic relationships between multiple time series, as these models demonstrated the highest consistency and maximum likelihood with the examined data compared to other selected models. Vector Autoregressive (VAR) models are employed to capture linear dependencies among multiple time series (Sims, 1980). In the context of GARCH-VAR, VAR is used to model the relationships between the time series, while GARCH investigates the dynamic relationships of the model's volatility. Meanwhile, the BEKK-VAR model integrates the BEKK approach, which provides a systemic view of estimating GARCH models, with VAR models. This model captures the dependencies between the time series using VAR while simultaneously examining correlations and dynamic volatilities through the BEKK specifications (Asai, 2015). Furthermore, the Threshold GARCH (TARCH) model can be appended to the aforementioned model, examining the effects of negative and positive shocks on volatility. The TARCH model expands the standard GARCH framework by incorporating different effects for negative and positive shocks (Zhao *et al*., 2019).

Bivariate GARCH-VAR: This approach combines the VAR model to capture the relationships between the series with a bivariate GARCH model to consider the conditional volatilities and correlations between the series. This model is useful when there is a need to model the joint behavior of multiple time series with time-varying volatilities.

The mean and error GARCH model for the returns of the Round Fandoghi pistachio commodity deposit market ($r_{c,t}$) and the Round Fandoghi pistachio futures market ($r_{f,t}$) are calculated as equation (9).

$$\begin{cases} r_{c,t} = \mu_c + e_{c,t} \\ r_{f,t} = \mu_c + e_{f,t} \end{cases} \Rightarrow \begin{cases} e_{c,t} = \sigma_{c,t} z_{c,t} \\ e_{f,t} = \sigma_{f,t} z_{f,t} \end{cases} \Rightarrow \begin{cases} z_{c,t} \sim N_{i.i.d}(0,1) \\ z_{f,t} \sim N_{i.i.d}(0,1) \end{cases} \quad (9)$$

Where $\sigma_{i,t}$ represents the standard deviation (volatility) of contract i and $z_{i,t}$ are standard normal variables ($\forall i = c, f$).

The conditional variance-covariance matrix H_t is expressed in equation (10):

$$H_t = \begin{bmatrix} \sigma^2_{cc,t} & \sigma_{cf,t} \\ \sigma_{cf,t} & \sigma^2_{ff,t} \end{bmatrix} \quad (10)$$

The conditional variances and covariances in the bivariate GARCH model are typically modeled using a GARCH process. A Bivariate GARCH (1,1) is estimated through the following set of equations (11):

$$\begin{cases} \sigma^2_{cc,t} = \gamma_{cc} + \alpha_{cc} e^2_{c,t-1} + \beta_{cc} \sigma^2_{cc,t-1} \\ \sigma^2_{ff,\mathrm{t}} = \gamma_{ff} + \alpha_{ff} e^2_{f,t-1} + \beta_{ff} \sigma^2_{ff,t-1} \\ \sigma_{cf,t} = \gamma_{cf} + \alpha_{cf} e_{c,t-1} e_{f,t-1} + \beta_{cf} \sigma_{cft-1} \end{cases} \quad (11)$$

Where γ_{ij} are the intercept values, α_{ij} are the lag coefficients of the error term from the mean model, and β_{ij} are the lag coefficients of the variance-covariance. Using the estimated values for the conditional variance of the log price difference of the futures contract $\widehat{H}_{ff}$ and the conditional covariance between the log price difference of the futures contract and the log price difference of the commodity deposit $\widehat{H}_{cf}$, the hedge ratio between the two contracts can be derived using equation (12):

$$\beta = \widehat{H}_{cf} / \widehat{H}_{ff} \quad (12)$$

Considering that the estimated conditional variance-covariance matrix is time-dependent, the computational risk hedge ratio obtained from this method is also time-dependent.

The BEKK-GARCH model is one of the variants of the bivariate GARCH models used to model conditional volatilities and covariances between two-time series. This model was developed by Baba, Engle, Kraft, & Kroner (1990), with the name BEKK derived from the initials of their last names (Engle & Kroner, 1995). The conditional mean and conditional variance-covariance equations for this model are also estimated using equations (9) and (11), and the optimal hedge ratio is obtained from equation (12). The only difference from the bivariate GARCH model

lies in the computation of the variance-covariance matrix H_t, which is obtained as follows in equation (13):

$$H_t = \Gamma'\Gamma + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B \quad (13)$$

Where H_t is the 2×2 variance-covariance matrix at time t, e_{t-1} is the lag of the error components, Γ is a lower triangular matrix, A represents lagged shock effects, and B represents lagged variance and variance-covariance effects. In other words, the matrices Γ, A, and B are the parameter matrices of the variance-covariance model, estimated using equation (11).

The mean and error model of the Vector Autoregressive (VAR) model is computed as shown in equation (14):

$$\begin{pmatrix} r_{c,t} \\ r_{f,t} \end{pmatrix} = \begin{pmatrix} \alpha_c \\ \alpha_f \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} \beta_{cc,i} & \beta_{cf,i} \\ \beta_{fc,i} & \beta_{ff,i} \end{pmatrix} \begin{pmatrix} r_{c,t-1} \\ r_{f,t-1} \end{pmatrix} + \begin{pmatrix} e_{c,t} \\ e_{f,t} \end{pmatrix} \Rightarrow E_t = H_t^{\frac{1}{2}} z_t, z_t \sim N(0,1) \quad (14)$$

Where the conditional variance-covariance matrix H_t for the GARCH-VAR model is also obtained using equations (10) and (11), while for the BEKK-VAR model, this matrix is computed using equation (13).

To incorporate threshold effects (TARCH) into either of the aforementioned models, the diagonal matrix Θ can be added to equation (13). This matrix adjusts the volatility model in such a way that the impact of negative shocks (e.g., a decrease in Round Fandoghi pistachio prices) on future volatility may not be equivalent to the impact of positive shocks. This aspect is particularly relevant in financial markets, as negative returns may induce greater variations in volatility compared to positive returns of the same magnitude. Consequently, equation (15) can be used to compute the variance-covariance matrix. H_t for the bivariate model:

$$H_t = \Gamma'\Gamma + A'e_{t-1}e'_{t-1}A + \Theta(E_{t-1}E_{t-1}^{<0})(E_{t-1}E_{t-1}^{<0})'\Theta' + B'H_{t-1}B \quad (15)$$

Additionally, it is noteworthy that equation (15) can be reformulated for the bivariate model in this study as shown in equation (16):

$$\begin{cases} \sigma_{cc,t}^2 = \gamma_{cc} + \alpha_{cc}^2 e_{c,t-1}^2 + \theta_{cc}^2 e_{c,t-1}^2 e_{c,t-1}^{<0} + \beta_{cc}^2 \sigma_{cc,t-1}^2 \\ \sigma_{ff,t}^2 = \gamma_{ff} + \alpha_{ff}^2 e_{f,t-1}^2 + \theta_{ff}^2 e_{c,t-1}^2 e_{c,t-1}^{<0} + \beta_{ff}^2 \sigma_{ff,t-1}^2 \\ \sigma_{cf,t} = \gamma_{cf} + \alpha_{cf}\alpha_{fc} e_{c,t-1} e_{f,t-1} + \theta_{cc}\theta_{ff} e_{c,t-1} e_{c,t-1}^{<0} e_{f,t-1} e_{f,t-1}^{<0} + \beta_{cc}\beta_{ff}\sigma_{cft-1} \end{cases} \quad (16)$$

Kroner and Ng (1998) argued that it is possible to achieve minimal risk for a commodity portfolio using a multivariate GARCH model under the assumption that the expected return ratio for each asset is zero. Equation (17) is utilized to calculate the commodity portfolio of two contracts: the Round Fandoghi pistachio commodity deposit (c) and Round Fandoghi pistachio futures (f). Here, $w_{cf,t}$ denotes the weight of product c in the combination of products c and f, with the weight of product f equal to $1 - w_{cf,t}$. $\sigma_{cf,t}$ represents the conditional covariance of products c and f, while $\sigma_{cc,t}^2$ and $\sigma_{ff,t}^2$ are the variances of products c and f, respectively. This commodity portfolio is frequently utilized by investment managers for optimal portfolio selection, and this study employs this portfolio to analyze the selection of an appropriate product mix to mitigate trading risks and resource exposure (Zhao *et al.*, 2019).

$$w_{cf,t} = \begin{cases} 0 & w_{cf,t} < 0 \\ \frac{\sigma_{ff,t}^2 - \sigma_{cf,t}}{\sigma_{cc,t}^2 - 2\sigma_{cf,t} + \sigma_{ff,t}^2} & 0 \le w_{cf,t} \le 1 \\ 1 & w_{cf,t} > 1 \end{cases} \quad (17)$$

This paper examines the price risk hedging of two contracts: Round Fandoghi pistachio futures and commodity deposit (spot) from October 19, 2018, to January 18, 2022.

Results and Discussion

Table 1 presents the results of the seasonal unit root test for daily data of pistachio contracts. This test examines the existence of unit roots at seasonal and non-seasonal frequencies, specifically employing the HEGY method (Hylleberg *et al.*, 1990). In this table, frequency 0 represents the non-seasonal trend, indicating the presence of a unit root in the time series. The frequencies $2\pi/6$ and $10\pi/6$ refer to seasonal patterns with two or multiple cycles, while frequencies $4\pi/6$ and $8\pi/6$ correspond to

specific seasonal fluctuations that may occur over shorter or longer periods. Frequency π\piπ denotes semiannual fluctuations.

For the return on the commodity deposit contract at frequency 0, the test statistic is -2.70, which is significant at the 10% level. This result suggests that the non-seasonal trend in the commodity deposit return is somewhat stable, with a possible unit root presence in this series. At frequencies 2π/6 and 10π/6, the test statistic is 2.68, which is significant at the 1% level, indicating strong and stable seasonal fluctuations at these frequencies. At frequencies 4π/6 and 8π/6, the test statistic is 3.33, also significant at the 1% level, showing strong seasonal fluctuations at these frequencies. At frequency π\piπ, the test statistic is -2.24, which is not interpretable at any significance level, indicating weak semiannual fluctuations in the commodity deposit return. Additionally, for all seasonal frequencies, the test statistic is 3.49, significant at the 1% level, indicating strong and stable seasonal fluctuations across all seasonal frequencies. Finally, for all frequencies, the test statistic is 4.24, which is significant at the 5% level, showing that when all frequencies are considered, the time series fluctuations are generally stable.

The existence of a seasonal unit root in products such as pistachios is due to their natural growth and harvest cycles. Pistachio trees flower in spring, fruit growth occurs in summer, and they are harvested in late summer to early fall. This natural cycle makes pistachio supply highly season-dependent. On the other hand, pistachio demand can also be seasonal, increasing around specific occasions, such as Nowruz and other festive seasons. Thus, both pistachio supply and demand follow seasonal patterns, impacting market prices and fluctuations (Rezaei *et al*., 2021).

For the futures contract return, the test statistic at frequency 0 is -2.96, which is significant at the 5% level, indicating a unit root in the non-seasonal trend of the futures return. At frequencies 2π/6 and 10π/6, the test statistic is 5.06, significant at the 1% level, reflecting very strong seasonal fluctuations at these frequencies. At frequencies 4π/6 and 8π/6, the test statistic is 4.14, significant at the 1% level, indicating very strong seasonal fluctuations. At frequency π, the test statistic is -2.41, which is not interpretable at any significance level, showing weak semiannual fluctuations in the future return. For all seasonal frequencies, the test statistic is 4.91, significant at the 1% level, denoting strong and stable seasonal fluctuations, and finally, for all frequencies, the test statistic is 5.56, significant at the 1% level, indicating stable fluctuations in the futures return time series.

In summary, both time series (commodity deposit contract return and futures contract return) exhibit significant seasonal and non-seasonal fluctuations, but the intensity of these fluctuations is higher in futures returns. For both series, seasonal fluctuations are much stronger than non-seasonal ones, yet semiannual fluctuations (frequency π) are weak in both series. Overall, seasonal fluctuations are a key factor in analyzing time series returns on contracts, and these fluctuations are stronger in futures contracts compared to commodity deposits.

Table 2 provides the regression coefficients and results for the returns on the commodity deposit contract ($r_{s,t}$) and the futures contract ($r_{f,t}$). The intercept in both equations is 0.01, with an insignificant standard error, indicating a lack of statistical significance. This suggests that the dependent variables, on average, do not exhibit significant changes in the absence of other effects.

Table 1- Results of the seasonal unit root test for 6 periods using the HEGY method (Hylleberg *et al*., 1990) for daily data of Round Fandoghi pistachio contracts

Seasonal and Non- Seasonal frequencies	Commodity Depositary Receipt Returns	Future Returns	Critical values in Significance Levels		
	Test Statistic	Test Statistic	1%	5%	10%
Frequency 0	-2.70*	-2.96**	-3.43	-2.85	-2.56
Frequency $2\pi/6$ and $10\pi/6$	2.68***	5.06***	2.68	1.17	0.74
Frequency $4\pi/6$ and $8\pi/6$	3.33***	4.14***	2.68	1.17	0.74
Frequency π	-2.24	-2.41	-3.43	-2.85	-2.56
All seasonal frequencies	3.49***	4.91***	3.15	2.07	1.68
All frequencies	4.24**	5.56***	4.4	3	2.44
Akaike info criterion	-4.12	-4.95			
Schwarz criterion	-2.64	-4.12			

*, **, and *** indicate significance at the levels of 90, 95, and 99 percent, respectively.

The coefficient of the previous period's return on the commodity deposit contract ($r_{s,t-1}$) for the commodity deposit return itself is negative and significant at the 99% level (-0.10, with a standard error of 0.035). This result implies that an increase in the commodity deposit return in the prior period leads to a reduction in the current period's return. However, this coefficient is not significant for the futures contract return.

The coefficient of the previous period's futures contract return ($r_{f,t-1}$) for the commodity deposit return is positive and highly significant at the 99% level (0.19, with a standard error of 0.036), indicating a strong positive effect. This coefficient is not significant for the current period's future return. The coefficient of $r_{f,t-2}$ for the commodity deposit return is positive and significant at the 90% level (0.07, with a standard error of 0.036), indicating that the futures contract return from two periods ago has a weak positive effect on the commodity deposit return. However, this coefficient is not significant for the future return.

The coefficient of $r_{f,t-3}$ for the commodity deposit return is positive and significant at the 95% level (0.09, with a standard error of 0.034). This suggests that the futures return three periods ago had a positive impact on the commodity deposit return. For the future return, this coefficient is not significant.

The coefficients of $r_{f,t-4}$, $r_{f,t-5}$, and $r_{f,t-6}$ for both the commodity deposit and futures returns are generally not significant, indicating that returns from four, five, and six periods ago have minimal or no meaningful impact on the current returns.

The t-statistic of the error term is significant at the 99% level (4.00, with a standard error of 0.528), showing the significance of the disturbance parameters and supporting the use of the Student's t-distribution for this data. The Akaike, Schwartz, and Hannan-Quinn criteria values are lower compared to competing models, indicating a good model fit. Specifically, the Akaike index is -10.54, and the Schwartz index is -10.37, highlighting that the model is relatively simple and explains the data effectively.

Table 3 continues the results from Table 2, showing significant and positive intercepts for both the commodity deposit and futures contract returns. This indicates that volatility persists in the data even in the absence of external shocks. The shock coefficients for both variables are significantly positive and high (0.28 for commodity deposit returns and 0.66 for futures returns), implying that shocks introduced into the system have a substantial impact on the volatility of both return types.

The threshold coefficient for the commodity deposit return is significant and positive (0.29 with a standard error of 0.087), suggesting that higher-than-threshold volatility has a stronger influence on future volatility. However, the threshold coefficient for the futures return is not significant, potentially indicating that volatility effects in this case are less dependent on a specific threshold.

Table 2- Results of the bivariate vector autoregressive generalized autoregressive conditional heteroskedasticity model with threshold effects (BEKK-VAR-TARCH)

Variable	Commodity Depositary Receipt Returns Coefficient (Std. Error)	Future Returns Coefficient (Std. Error)
Intercept	0.01(0)	0.01(0.001)
$r_{s,t-1}$	-0.10(0.035)***	0.02(0.016)
$r_{f,t-1}$	0.19(0.036)***	0.03(0.039)
$r_{f,t-2}$	0.07(0.036)*	0.05(0.039)
$r_{f,t-3}$	0.09(0.034)**	-0.01(0.036)
$r_{f,t-4}$	0.06(0.036)	0.01(0.034)
$r_{f,t-5}$	0.06(0.035)	0.04(0.033)
$r_{f,t-6}$	0.05(0.036)	-0.03(0.03)
t-student of error distribution	4.00(0.528)***	
Log-likelihood	3598.91	
Avg. log-likelihood	2.65	
Akaike info criterion	-10.54	
Schwarz criterion	-10.37	
Hannan-Quinn criterion.	-10.47	

The symbols *, **, and *** indicate significance at the levels of 90, 95, and 99 percent, respectively.

The lagged variance coefficients for both the commodity deposit and futures returns are highly significant and substantial (0.96 and 0.84, respectively). These coefficients demonstrate that past volatility significantly impacts current volatility, with persistence in volatility over time through an autoregressive process.

The BEKK-VAR-TARCH model effectively captures the interplay of volatilities between the commodity deposit and futures contracts, showing that these two variables exert significant mutual influence on each other. The significant impacts of shocks and variance lag on both variables underscore the stability and transmission of volatility within these markets.

These findings emphasize the importance of closely monitoring past shocks and volatility in financial markets, as these factors notably influence future market behavior. By accounting for threshold effects, the BEKK-VAR-TARCH model provides a more precise representation of the complex market dynamics.

Table 3- Results of the variance model of the bivariate vector autoregressive generalized autoregressive conditional heteroskedasticity model with threshold effects (BEKK-VAR-TARCH)

Parameter	Commodity Depositary Receipt Returns Coefficient (Std. Error)	Future Returns Coefficient (Std. Error)	Covariance of Returns Coefficient (Std. Error)
Intercept	0.01(0.001)	0.01(0.001)***	0.01(0.001)
Shock Effect	0.28(0.047)***	0.66(0.063)***	
Threshold	0.29(0.087)***	0.17(0.185)	
Variance Lag Effect	0.96(0.011)***	0.84(0.018)***	

The symbols *, **, and *** indicate significance at the levels of 90, 95, and 99 percent, respectively.

Table 4 summarizes the trend of the optimal ratio for integrating commodity deposit contracts of Round Fandoghi pistachios with futures contracts. This optimal ratio represents the share of commodity deposit contracts within a two-asset portfolio that includes both commodity deposit and futures contracts. The table presents the average ratio values across different days of the week and seasons, along with their standard errors.

In spring, for the month (April), the share of commodity deposit contracts at the start of the week (Saturday) is 0.55, increasing to 0.73 by midweek, and then decreasing to 0.60 by the week's end. This notable increase on Tuesdays and Wednesdays indicates a midweek preference for commodity deposit contracts. In May, the share remains consistently high, ranging from 0.78 to 0.84, reflecting a strong preference for commodity deposit contracts,

with these values being statistically significant. In June, the share stabilizes between 0.64 and 0.75, indicating a consistent preference for commodity deposit contracts during this month.

In summer, (July) shares for commodity deposit contracts lower, ranging from 0.45 to 0.57, suggesting a reduced preference, with these values generally lacking statistical significance. In August, the share rises slightly to a range of 0.52 to 0.69, possibly due to market volatility or seasonal demand changes. September marks the beginning of the pistachio harvest season, with ratios higher between 0.67 and 0.76, indicating increased demand for commodity deposit contracts as summer concludes.

During autumn, (October) relatively high shares ranging from 0.66 to 0.76 develops, with most values statistically significant, which may reflect a growing preference for commodity deposit contracts. In November, the share remains elevated, ranging from 0.60 to 0.69, indicating stable demand. December records the highest values, between 0.72 and 0.77, representing peak demand for commodity deposit contracts, further supported by statistical significance.

In winter, the ratios in January, fluctuate between 0.55 and 0.68, likely due to seasonal or market fluctuations. In February, the ratios are very high, ranging from 0.79 to 0.86, with all values statistically significant, indicating this as the peak period for commodity deposit contracts. Ratios decrease in March, ranging from 0.54 to 0.67, possibly due to seasonal factors or the approaching fiscal year-end.

Overall, the results from Table 4 demonstrate that seasonal fluctuations result in a higher optimal share of commodity deposit contracts during spring and winter, while there is a noticeable decrease in summer. These seasonal changes likely stem from varying market demand across seasons. The statistically significant values observed on many days reinforce the reliability of these findings, making them crucial for optimizing investment portfolios. Additionally, the optimal ratio fluctuates across different weekdays, potentially due to daily factors such as market news or shifts in investor expectations.

This analysis empowers investors to make informed decisions regarding portfolio allocations, capitalizing on seasonal and daily market fluctuations. By leveraging insights on changes in the optimal ratios for Round Fandoghi pistachio commodity deposit contracts, investors can enhance their risk management and portfolio composition strategies. Observable shifts in these ratios, particularly the increases during spring and winter, highlight heightened demand during these periods, presenting profit opportunities. Furthermore, daily patterns, such as midweek increases, allow investors to adjust their strategies dynamically.

In summary, the significant seasonal variations and changes in the optimal ratios equip investors to capitalize on unique seasonal opportunities and make more accurate market forecasts. This builds investor confidence and facilitates data-driven decision-making based on robust statistical results.

Conclusion

In this study, the optimal hedge ratio for Round Fandoghi pistachio commodity deposit receipts and futures contracts were examined. Results from the BEKK-VAR-TARCH model demonstrated that daily and seasonal volatilities significantly influence returns and hedge ratios. Notably, substantial fluctuations were observed on specific days and within particular periods, affecting speculative and investment decisions in the commodity exchange market. These findings underscore the importance of choosing strategies that align with market conditions and accurately timing market entry to optimize profitability.

Table 4- Summary of the trend changes in the optimal ratio of commodity deposit contracts for Round Fandoghi pistachios in the combination of commodity deposit and futures contracts

Season	Mouth	Week day	The average share of commodity deposit contracts from Portfolio (Std. Error)	Season	Mouth	The average share of commodity deposit contracts from Portfolio (Std. Error)
Spring	April	Saturday	0.55 (0.108)	Fall	October	0.73 (0.104) **
		Sunday	0.65 (0.092) *			0.76 (0.088) **
		Monday	0.71 (0.087) **			0.69 (0.122) *
		Tuesday	0.73 (0.081) **			0.67 (0.113) *
		Wednesday	0.73 (0.089) **			0.66 (0.082) **
		Thursday	0.60 (0.111) *			0.72 (0.088) **
	May	Saturday	0.83 (0.034) ***		Novemmber	0.64 (0.095) *
		Sunday	0.82 (0.047) ***			0.63 (0.095) *
		Monday	0.78 (0.062) ***			0.69 (0.105) *
		Tuesday	0.83 (0.046) ***			0.67 (0.096) *
		Wednesday	0.82 (0.046) ***			0.60 (0.088) *
		Thursday	0.84 (0.038) ***			0.64 (0.092) *
	June	Saturday	0.64 (0.104) *		December	0.72 (0.077) **
		Sunday	0.72 (0.106)*			0.73 (0.080)**
		Monday	0.75 (0.104)**			0.74 (0.073)**
		Tuesday	0.66 (0.116)*			0.72 (0.075)**
		Wednesday	0.72 (0.112)*			0.77 (0.066)***
		Thursday	0.64 (0.103)*			0.76 (0.071)**
Summer	July	Saturday	0.55 (0.151)	Winter	January	0.62 (0.103)*
		Sunday	0.48 (0.144)			0.56 (0.065)**
		Monday	0.45 (0.161)			0.62 (0.077)**
		Tuesday	0.49 (0.152)			0.66 (0.103)*
		Wednesday	0.55 (0.151)			0.68 (0.115)*
		Thursday	0.57 (0.144)			0.55 (0.124)
	August	Saturday	0.65 (0.107)*		Februray	0.79 (0.075)***
		Sunday	0.68 (0.098)*			0.79 (0.068)***
		Monday	0.69 (0.098)**			0.84 (0.054)***
		Tuesday	0.66 (0.104)*			0.86 (0.052)***
		Wednesday	0.52 (0.110)			0.79 (0.069)***
		Thursday	0.53 (0.106)			0.81 (0.066)***
	September	Saturday	0.67 (0.109)*		March	0.65 (0.129)
		Sunday	0.72 (0.095)**			0.64 (0.132)
		Monday	0.70 (0.097)**			0.67 (0.115)*
		Tuesday	0.72 (0.109)*			0.66 (0.123)*
		Wednesday	0.76 (0.110)*			0.58 (0.156)
		Thursday	0.70 (0.121)*			0.54 (0.141)

The symbols *, **, and *** indicate significance at the levels of 90, 95, and 99 percent, respectively.

The results suggest that utilizing volatility models, especially during unstable market conditions, consistently enhances investment decision-making and mitigates potential risks. Similar findings have been reported in international financial markets regarding the impact of seasonal and daily volatilities on hedge ratios, highlighting the market volatility as a global phenomenon warranting special consideration in various countries.

Based on the present study's findings, it is recommended that investors and market participants leverage financial instruments, such as futures contracts and commodity deposit receipts, to manage existing risks and incorporate seasonal volatilities and specific weekdays into their investment strategies. Additionally, offering educational programs and creating information platforms to increase investor awareness of market behavior and volatility can improve decision-making and market efficiency. These initiatives can bolster investments and reduce risks associated with market fluctuations.

Several policy recommendations to enhance the performance of the Round Fandoghi

pistachio market and improve decision-making efficiency for speculators and investors in the commodity exchange market for the Round Fandoghi pistachio are as follows:

1. Strengthening and Managing Seasonal Volatilities: Given the importance of seasonal volatilities in both time series (commodity deposit contract returns and futures contract returns), it is recommended that policymakers and market participants conduct a more detailed analysis of these volatilities and plan to address unusual seasonal fluctuations. These plans could include launching derivative financial instruments, such as options or futures contracts, that aid in managing volatility risks.
2. Supporting Hedging Tools: Considering the significant impact of shocks and past volatilities on contract returns, the development and promotion of hedging tools, like futures and other derivatives, can help investors better manage risks arising from fluctuations. This is especially crucial during periods of high market volatility.
3. Incorporating Seasonal and Daily Patterns in Portfolio Composition: The results indicate that the optimal ratio for commodity deposit contracts varies across different seasons and weekdays. Policymakers and investors should be mindful of these changes and, at appropriate times, adjust their portfolio composition based on a detailed analysis of seasonal and daily changes. This strategy aids in risk reduction and yield enhancement.

References

1. Ahangari, S., Mojaverian, S.M., & Hosseini Yekani, S.A. (2017). Prioritization of the factors affecting the success of a commodity in agricultural ring of Iran mercantile exchange. *Journal of Agricultural Economics and Development*, *31*(1), 27–35. https://doi.org/10.22067/JEAD2.V31I1.56950
2. Alausa, W.B. (2014). Three essays on the application of the markov switching multifractal model [Doctor of philosophy, department of economics university of Alberta]. In *ERA*. https://doi.org/10.7939/R39G5GN72
3. Ameur, H. Ben, Ftiti, Z., & Louhichi, W. (2022). Revisiting the relationship between spot and futures markets: evidence from commodity markets and NARDL framework. *Annals of Operations Research*, *313*(1), 171–189. https://doi.org/10.1007/s10479-021-04172-3
4. Amjadi, A., Hosseini Yekani, S.A., & Ahmadi Kaliji, S. (2017). The role of agricultural commodity exchange on hedging (Case study: Selected agricultural product). *Journal of Agricultural Economics and Development*, *25*(98), 1–17. https://sid.ir/paper/24596/en
5. Asai, M. (2015). Bayesian Analysis of General Asymmetric Multivariate GARCH Models and News Impact Curves. *Journal of the Japan Statiatical Society*, *45*(2), 129–144. https://doi.org/10.14490/jjss.45.129
6. Baba, Y., Engle, R.F., Kraft, D.F., & Kroner, K.F. (1990). *Multivariate simultaneous generalized arch, department of economics, university of California at San Diego*.
7. Baghestani, A.A., Yazdani, S., & Ahmadian, M. (2016). The application of GMDH neural network approach in forecasting the price of soybean meal in Iran mercantile exchange. *Journal of Financial Economics (Financial Economics and Development), 9(33)*, *9*(33), 1–13. https://sid.ir/paper/ 229315/en
8. Borzabadi Farahani, M., Gholizadeh, M., & Chirani, E. (2021). Dynamic modeling of estimating the optimal hedge ratio of gold coin with saffron futures contracts. *Journal of Securities Exchange*, *14*(55), 5–37. https://doi.org/10.22034/jse.2020.11238.1450
9. Castro, T. del B., Osborn, D.R., & Taylor, A.M.R. (2012). On augmented Hegy tests for seasonal unit roots. *Econometric Theory*, *28*(5), 1121–1143. https://doi.org/10.1017/S0266466612000060
10. Chance, D.M. (1989). An introduction to options and futures. In *The Dryden Press, a division of*

Holt, Rinehart, and Winston, Inc. https://archive.org/details/isbn_0030284392
11. Chen, S.-S., Lee, C., & Shrestha, K. (2003). Futures hedge ratios: a review. *The Quarterly Review of Economics and Finance*, *43*(3), 433–465. https://doi.org/10.1016/S1062-9769(02)00191-6
12. Choudhry, T. (2009). Short-run deviations and time-varying hedge ratios: Evidence from agricultural futures markets. *International Review of Financial Analysis*, *18*(1–2), 58–65. https://doi.org/10.1016/j.irfa.2008.11.003
13. Edwards, F.R., & Ma, C.W. (1992). *Futures and Options*. McGraw-Hill. https://api.semanticscholar.org/CorpusID:152550058
14. Enders, W. (2014). Applied Econometric Time Series. In *Wiley*. https://bcs.wiley.com/he-bcs/Books?action=index&itemId=1118808568&bcsId=9288
15. Engle, R.F., & Kroner, K.F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory*, *11*(1), 122–150. https://doi.org/10.1017/S0266466600009063
16. Geman, H. (2005). Commodities and commodity derivatives modeling and pricing for agricultural, metals and energy. In *John Wiley & Sons, Ltd* (1st ed.). www.wiley.com/en-us/Commodities+and+Commodity+Derivatives%3A+Modeling+and+Pricing+for+Agriculturals%2C+Metals+and+Energy-p-9780470012185
17. Ghazali, A., Nasrabadi, M.B., & Nasrabadi, H.B. (2016). Identification of factors affecting lack of boom in the agricultural ring in Iran mercantile exchange. *Strategic Management Thought (Management Thought)*, *10*(1(19)), 181–214. https://doi.org/10.30497/SMT.2016.1872
18. Haj Seyed Javadi, S.M.R., & Heydari, R. (2022). Designing the most suitable hybrid model for forecasting the future price of saffron in the agricultural commodity exchange. *Iranian Journal of Agricultural Economics and Development Research*, *53*(4), 1023–1041. https://doi.org/10.22059/IJAEDR.2022.336850.669122
19. Han, L., Jin, J., Wu, L., & Zeng, H. (2020). The volatility linkage between energy and agricultural futures markets with external shocks. *International Review of Financial Analysis*, *68*. https://doi.org/10.1016/j.irfa.2019.01.011
20. Hylleberg, S., Engle, R.F., Granger, C.W.J., & Yoo, B.S. (1990). Seasonal integration and cointegration. *Journal of Econometrics*, *44*(1–2), 215–238. https://doi.org/10.1016/0304-4076(90)90080-D
21. *Iran Mercantile Exchange*. (2024. August). https://en.ime.co.ir
22. Johnson, L.L. (1960). The theory of hedging and speculation in commodity futures. *The Review of Economic Studies*, *27*(3), 139–151. https://doi.org/10.2307/2296076
23. Kashiri Kolaei, F., & Hosseni Yekani, S.A. (2016). Investigating the effects of commodity exchange on competition of pistachios suppliers in Iran. *Iranian Journal of Agricultural Economics and Development Research*, *472*(3), 581–587. https://sid.ir/paper/146267/en
24. Kavoosi Kalashami, M., & Kavoosi Kalashami, M. (2017). Price relationships and spillover effects of price volatilities in Iran's rice market. *International Journal of Agricultural Management and Development*, *7*(4), 429–438. magiran.com/p1773999
25. Li, M.-Y.L. (2012). Modeling the natural gas spot-futures markets as a regime switching vector error correction model. *Energy Sources, Part B: Economics, Planning, and Policy*, *7*(3), 301–313. https://doi.org/10.1080/15567240903117609
26. Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77. https://doi.org/10.2307/2975974
27. Miremadi, S.A., Chizari, A., Yazdani, S., Rafiee, H., & Mohtashami, T. (2021). Investigating the efficiency of Negin saffron futures contract in Iran Mercantile Exchange. *Iranian Journal of Agricultural Economics and Development Research*, *52*(4), 851–862. https://doi.org/10.22059/IJAEDR.2021.317027.669001
28. Mohammadi, M., Mohammadi, H., & Fakari, B. (2016). The impact of macroeconomic variables on the volatility of agricultural prices in the Iran mercantile exchange (the case of barley). *Journal of Agricultural Economics and Development*, *24*(95), 1–23. https://www.sid.ir/paper/24562/fa

29. Moumouni, Z. (2016). *Modeling and Hedging Strategies for Agricultural Commodities* [Université Montpellier]. https://doi.org/tel-01563222
30. Myers, R.J., & Thompson, S.R. (1989). Generalized optimal hedge ratio estimation. *American Journal of Agricultural Economics*, *71*(4), 858–868. https://doi.org/10.2307/1242663
31. Pakdaman, N., Javanshah, A., & Nadi, M. (2023). Investigating the effect of climate change on pistachio yield. *Research in Horticultural Sciences*, *2*(2), 177–190. https://doi.org/10.22092/rhsj.2023.360550.1034
32. Pishbahar, E., Baghestani, M., & Dashti, Gh. (2018). Application of binomial tree in determining the price of an Asian option and calculation of risk-sensitive parameters (Case study: Soybean meal and corn). *Journal of Agricultural Economics and Development*, *32*(1), 1–16. https://doi.org/10.22067/JEAD2.V32I1.62744
33. Rezaei, H., Zare, M., & Falah Qalhari, G.A. (2021). The effect of climatic parameters on pistachio phenology according to day degree in Gonabad city. *Natural Geography*, *52*(13), 1–14. https://journals.iau.ir/article_682962_c2c2cd866f23fce77964a291b304880b.pdf
34. Rezitis, A.N., Andrikopoulos, P., & Daglis, T. (2024). Assessing the asymmetric volatility linkages of energy and agricultural commodity futures during low and high volatility regimes. *Journal of Futures Markets*, *44*(3), 451–483. https://doi.org/10.1002/fut.22477
35. Schneider, L., & Tavin, B. (2024). Seasonal volatility in agricultural markets: modeling and empirical investigations. *Annals of Operations Research*, *334*(1–3), 7–58. https://doi.org/10.1007/s10479-021-04241-7
36. Shen, F. (2020). *Spillover Effects from Swap Dealers and Index Traders on Agricultural Commodity Futures, a BEKK-MGARCH Approach* [Master of Science, Texas A&M University]. https://oaktrust.library.tamu.edu/handle/1969.1/192881
37. Siegel, D.R., & Siegel, D.F. (1990). *The futures markets: Arbitrage, risk management, and portfolio strategies*. Probus Pub Co. https://archive.org/details/futuresmarketsar0000sieg/page/n3/mode/2up
38. Sims, C.A. (1980). Macroeconomics and Reality. *Econometrica*, *48*(1), 1–76. https://doi.org/10.2307/1912017
39. Singhal, S., & Biswal, P.C. (2021). Dynamic commodity portfolio management: A regime-switching VAR model. *Global Business Review*, *22*(2), 532–549. https://doi.org/10.1177/0972150918811705
40. Tajabadipour, A., & Afarasteh, M. (2022). Preparation of pistachio orchards to reduce spring frost damage. *Pistachio World*, *7*(78), 51–53.
41. Witt, H.J., Schroeder, T.C., & Hayenga, M.L. (1987). Comparison of analytical approaches for estimating hedge ratios for agricultural commodities. *Journal of Futures Markets*, *7*(2), 135–146. https://doi.org/10.1002/fut.3990070204
42. Yahya, M., Oglend, A., & Dahl, R.E. (2019). Temporal and spectral dependence between crude oil and agricultural commodities: A wavelet-based copula approach. *Energy Economics*, *80*, 277–296. https://doi.org/10.1016/j.eneco.2019.01.011
43. Zhang, Z., & Chuan, L.I. (2006). Country-specific factors and the pattern of intra-industry trade in China's manufacturing. *Journal of International Development*, *18*(8), 1137–1149. https://doi.org/ 10.1002/jid.1288
44. Zhao, L., Meng, Y., Zhang, Y., & Li, Y. (2019). The optimal hedge strategy of crude oil spot and futures markets: Evidence from a novel method. *International Journal of Finance & Economics*, *24*(1), 186–203. https://doi.org/10.1002/ijfe.1656
45. Zhao, R., Diao, G., & Chen, S. (2019). Study on the price fluctuation and dynamic relationship between log and sawn timber. *Forest Products Journal*, *69*(1), 34–41. https://doi.org/10.13073/ FPJ-D-17-00048

Appendix

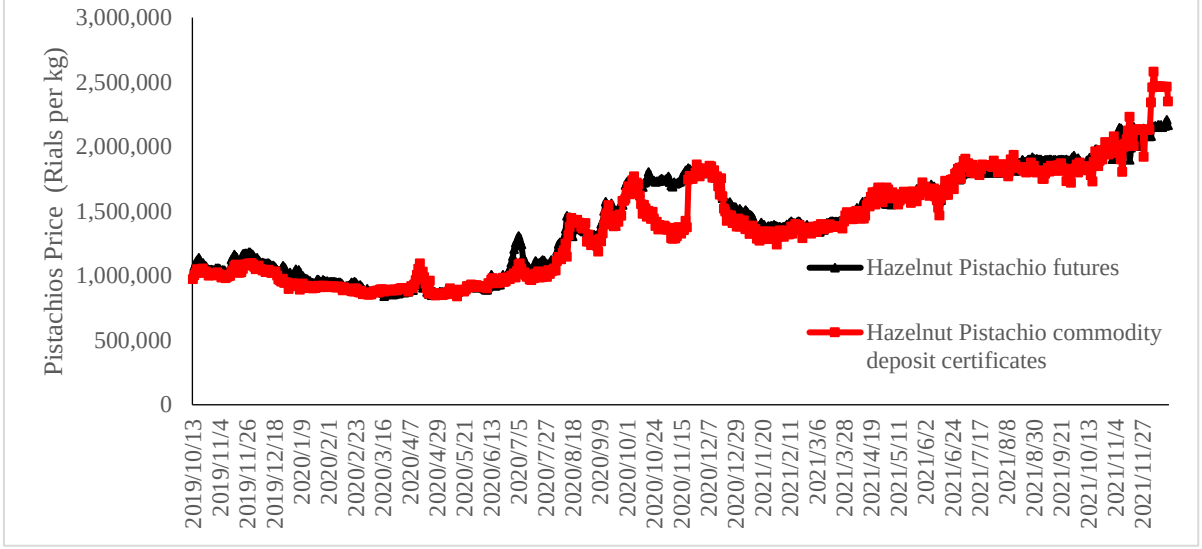

Figure A1- The Price of Future and Commodity Depositary Receipt Contracts in Iran Mercantile Exchange (Iran Mercantile Exchange, 2024)

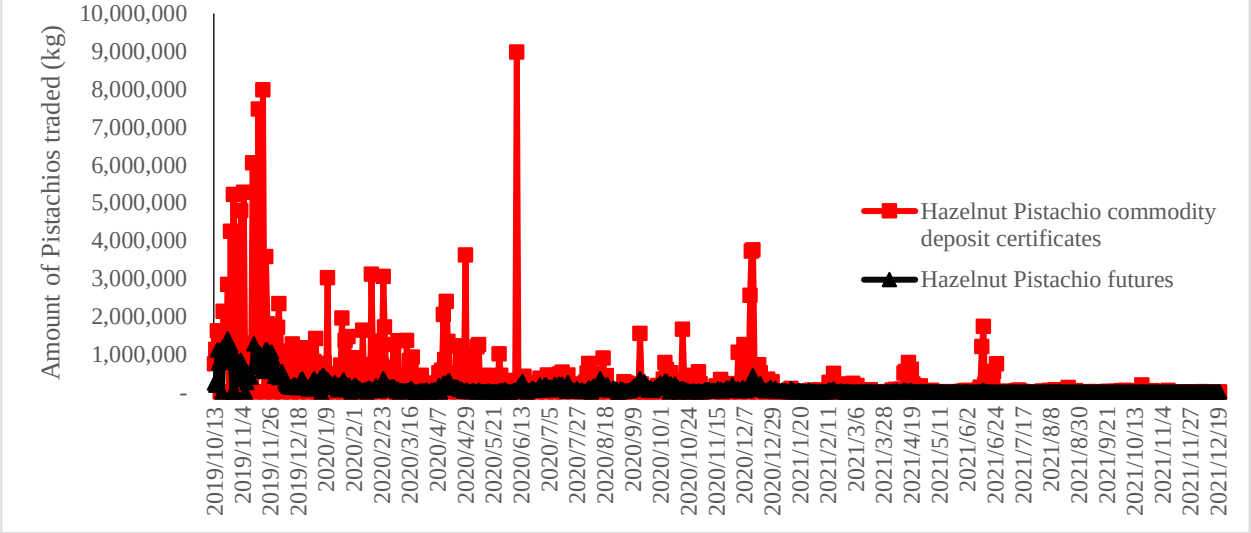

Figure A2- The Quantity of Future and Commodity Depositary Receipt Contracts in Iran Mercantile Exchange (Iran Mercantile Exchange, 2024)

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مقاله پژوهشی

جلد ۳۸، شماره ۴، زمستان، ۱۴۰۳، ص. ۴۱۱-۳۹۳

بررسی ریسک قراردادهای پسته فندقی در بازار بورس کالای ایران

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تاریخ دریافت: ۱۴۰۳/۰۵/۲۷

تاریخ پذیرش: ۱۴۰۳/۰۷/۲۸

چکیده

این مطالعه بر روی پوشش ریسک پسته فندقی با استفاده از قراردادهای آتی و سپرده سرمایه¬گذاری تمرکز دارد و تغییرات ریسک و انتخاب پرتفوی بهینه را از ۲۷ مهرماه ۱۳۹۷ تا ۲۸ دی‌ماه ۱۴۰۰ بررسی می‌کند. با استفاده از نظریه سبد کالایی مارکویتز، این مطالعه از مدل‌های اقتصادسنجی مختلفی از جمله تحلیل رگرسیون، مدل‌های GARCH و آزمون ریشه واحد فصلی برای تعیین سبد کالایی بهینه جهت پوشش ریسک استفاده می‌کند. نتایج کلیدی شامل نوسانات فصلی معنادار در فرکانس‌های مختلف است که نشان‌دهنده الگوهای فصلی قوی و پایدار است. تحلیل رگرسیون روابط معناداری بین بازده‌های گذشته و کنونی را نشان می‌دهد که تأثیر بازده‌های گذشته بر عملکرد کنونی را برجسته می‌کند. مدل‌های GARCH ضرایب مثبت معناداری برای اثرات شوک و وقفه‌های واریانس نشان می‌دهند که به معنای تأثیرات قابل توجه شوک‌ها و اثرات خودرگرسیونی قوی نوسانات گذشته بر نوسانات کنونی است. نسبت بهینه قراردادهای سپرده کالایی پسته فندقی بر اساس فصل و روز متغیر است که تقاضای بازار و ترجیحات سرمایه‌گذاران را منعکس می‌کند. این مطالعه چندین پیشنهاد سیاستی ارائه می‌دهد که عبارتند از؛ تقویت و مدیریت نوسانات فصلی از طریق مشتقات مالی، حمایت از ابزارهای پوشش ریسک، توجه به الگوهای فصلی و روزانه در ترکیب سبد کالایی، پایش و کنترل نوسانات در دوره‌های حساس و توسعه سیاست‌های حمایتی در ماه‌های کم نوسان. این پیشنهادها هدف دارند عملکرد بازار پسته فندقی را بهبود بخشیده و کارایی تصمیم‌گیری‌های سرمایه‌گذاری را افزایش دهند.

واژه‌های کلیدی: رفتار فصلی داده¬ها، سبد بهینه کالایی، نسبت بهینه پوشش ریسک

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https://doi.org/10.22067/jead.2024.89445.1289

Journal of Agricultural Economics & Development

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

Research Article
Vol. 38, No. 4, Winter 2025, p. 413-429

Compilation of Sustainable Agricultural Development Scenarios in Zayandeh-Rud River Watershed- Isfahan Province of Iran

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Received: 23-09-2024
Revised: 01-11-2024
Accepted: 17-11-2024
Available Online: 17-11-2024

How to cite this article:
Zarei Dastgerdi, Z., Kalantari, Kh., & Asadi, A. (2025). Compilation of sustainable agricultural development scenarios in Zayandeh-Rud River watershed- Isfahan province of Iran. *Journal of Agricultural Economics & Development*, *38*(4), 413-429. https://doi.org/10.22067/jead.2024.89627.1292

Abstract

The agricultural sector in developing countries plays an important role in promoting national development and rational policy making and strategic planning to advance the sustainable development of this sector are of main concerns of the relevant institutional actors. In this regard, the current research was conducted with the aim of identifying scenarios of sustainable agricultural development in the catchment area of Zayandeh River in Isfahan province. The present research was applied, of descriptive-survey type. The statistical population was experts related to agricultural development in the province. To collect data, library sources, questionnaires and interviews were used. Delphi method and interviews with elites and executives were used to identify the primary components and drivers effective on the sustainable development of agriculture in the Zayandeh River watershed of Isfahan province. The snowball technique was used to select the experts. Finally, 8 key drivers were identified and separated in order to explain the research variables in a strategic format. Based on this, in the section related to the expression of research priorities in two direct and indirect modes, these 8 key factors have been repeated in different priorities. Questionnaires were distributed among 25 experts. In this study, five plausible scenarios were identified for forecasting the future of sustainable agricultural development by considering potential outcomes based on key factors and their similarities or differences across the categories of favorable, static, and critical scenarios. Based on their total scores, which range from 85 to 109, two scenarios were identified as the most likely: one favorable scenario and one critical scenario.

Keywords: Agricultural development, Foresight, Scenario planning, Zayandeh-Rud watershed

https://doi.org/10.22067/jead.2024.89627.1292

Introduction

The agricultural sector in developing countries plays an important role in promoting national development and rational policy making and strategic planning to advance the sustainable development of this sector is one of the main concerns of the relevant institutional actors. The agricultural sector accounts for 7% of the gross national product, 14% of employment and providing food for more than 80% of the people in the society therefore, it plays an important role in the country's economy (Bahrami & Asadi, 2020). On one hand, the complexity of human-driven changes, variable environmental factors, and the unpredictability of the global economy impacting agricultural activities pose significant challenges. On the other hand, the strategic importance of food security and poverty reduction further intensifies the difficulties in achieving sustainable agricultural development. The growing trend of globalization of agricultural trade and extensive competition in this field, which has transformed the framework of market equilibrium, all components of the agricultural industry undergo fundamental and structural changes. The impact of environmental factors and climate change has already led to fundamental shifts in agriculture, and in the near future, it is certain to have the most destructive effects on agricultural activities. Considering the link of the listed components in the future, policymakers and practitioners in the field of agriculture, despite their lack of preparation, will face increasing and unpredictable challenges (Sharifzadeh & Hosseini, 2009). Therefore, it is necessary that the developed strategies to deal with these issues are based on comprehensive and optimal analysis which examines the main dimensions of agriculture and food sector in an integrated way. These patterns should create a tool for integrated and dynamic planning which can enable transparent cross-sectoral analyzes of policy effects and enable exploration of their long-term implications for social, economic, and environmental development (Fakari *et al.*, 2020). Due to the ever-increasing changes and transformations, relying on traditional planning methods is no longer the answer, and the heavy shadow of uncertainties and the emergence of discontinuous and surprising events change the situation in such a way that planning seems difficult. The lack of ability to predict the future as well as the complications caused by the changes have caused the emerging knowledge of foresight to enter the activities of planning and predicting developments (Zali & Atriyan, 2016). During this period, planners have adopted various approaches to address future challenges, depending on the time and location conditions, typically based on the analysis of past trends and the continuation of the current situation. However, today, the science of futurology has transformed scattered and fragmented studies on future planning into a well-established field with solid principles and foundations. Its role, in addition to analyzing past trends, is to explore, invent, and evaluate possible, probable, and desirable futures (Zali & Atriyan, 2016).

In agriculture, considering the future is essential for ensuring the strengthening and stability of the sector. A key and fundamental aspect of foresight studies in agriculture is the stability and growth of agricultural production, which should be accompanied by improvements in product quality. Additionally, serious attention must be given to creating a suitable platform for fostering sustainable agriculture in the country. Undoubtedly, planners and policy makers in the agricultural sector can use foresight to draw future prospects for the sustainable development of the agricultural sector and in this way, realize the capacity of directiveness expected from strategic policies in advancing the agricultural sector in accordance with situational considerations, national priorities and global developments. Accordingly, various researchers and international organizations, such as the FAO, have utilized foresight to shape future perspectives for the agricultural sector and related areas, including food security (Sharifzadeh & Hosseini, 2009). Futurism has a long history, with the United States and Japan

being among the pioneers in using this tool. However, in the last decade, nearly all countries worldwide have adopted it (Karamatzadeh, 2006). In Iran, some researchers have analyzed the future and designed scenarios in different fields. In other countries, studies have been done in the field of agricultural future research or agricultural research (Akrami *et al.*, 2021). An analysis of scientific sources reveals a strong need for extensive research in the field of future studies within the agricultural sector of the country. Below, some of the limited studies that have been conducted in this area are highlighted.

Jashari & Morad (2018) in research entitled "Development of macro-strategies for the development of the agricultural sector of Sistan and Baluchistan province", investigated the agricultural situation of this province with a future research approach. The authors identified the driving forces affecting the development and progress of agriculture and animal husbandry in the province and then they introduced five main drivers in the agricultural sector and five drivers in the livestock sector and tried to analyze the scenarios using the scenario method and then, in the form of each scenario, according to the upstream documents and previous studies, for the agricultural development of the province, they have expressed strategies such as the promotion of specialized and applied knowledge and the empowerment of human resources, the continuation of government investment, etc.

Fakari *et al.* (2020), in their research titled "Future Research of Iran's Wheat," examined the status of wheat up to the year 1420. Using the GBN scenario writing method with Scenario Wizard and Mic Mac software, and consulting a group of experts from universities, research centers, and managers of the country's wheat project in 2019, they explored the future of wheat research in the country. From eighteen possible scenarios, three were selected: "Forward to the Future" (the first scenario), "Never Changing" (the second scenario), and "Going Back to History" (the third scenario). These evaluations provided different future scenarios to help policymakers develop better planning strategies for the future of wheat production. Bagheri *et al.* (2020), in their article on the future research of the Agricultural Engineering and Technical Research Institute in 1404, focused on examining alternative futures for the institute as an active, knowledge-based research organization in agricultural technology. The GBN method was used to design the scenarios. Initially, the trends influencing the institute's research activities were identified, followed by the key uncertainties. After developing the scenario matrix, three scenarios were created: the "Traditional Future," the "Difficult Future," and the "Desirable Future." Asadi *et al.* (2021), in their research titled "Forecasting the Future of Australia's Digital Agriculture: Using Innovative Thinking to Predict the Impact of Research and Development Under Different Scenarios," explored the future of agriculture in Australia, focusing on the role of digital technology and its social and ethical implications. The study developed four scenarios to predict the future of agriculture in Australia. The findings indicate that these scenarios highlight potential changes in farm business models, decision-making processes, stakeholder involvement, and the inequalities introduced by new technologies, as well as other components of the food value chain. Gutzler *et al.* (2015), in their study of agricultural land use changes, assessed the sustainable and integrated effects of agricultural intensification scenarios in the federal state of Brandenburg, Germany, for the year 2025. The results of the research indicate that, in the comprehensive evaluation, agricultural intensification scenarios have a sustainable effect at the regional level. However, this intensification is accompanied by negative environmental and socio-economic impacts. Ajilore *et al.* (2018) explored the future of agricultural research and innovation in Africa. Using collaborative methods and examining the current and past agricultural situation, they proposed four possible future scenarios for agricultural research. The results of the scenario analysis indicated that African agriculture is evolving due to innovations. The

purpose of examining these scenarios with the involvement of stakeholders was to help the new generation of scientists, researchers, promoters, and innovators in the agricultural sector develop the necessary capacity for dialogue and strategic thinking regarding the future. Makal *et al*. (2017), in their study titled "Problems and Challenges of Agricultural Development (Case Study: Farmers of West Bengal)," highlighted several issues faced by agriculture in West Bengal, including problems with agricultural and rural infrastructure such as irrigation, soil, land, capital, labor, product storage, modern agricultural inputs, the environment, production, production costs, and price fluctuations. Similarly, a study by Nsikak & Kesit (2015) in Nigeria found that the challenges in the country's agricultural sector include climate change, outdated farming methods, weak infrastructure, and insufficient government support for research and development in agricultural technologies, which hinder production growth. Additionally, Nematollahi *et al.* (2016) analyzed the necessary measures for the environmental development of the agricultural sector in Jianshan using the SWOT method, concluding that the development of agriculture in the region is progressing well and that an aggressive strategy is the dominant development approach. Among the study's recommendations were eliminating the need for animal husbandry development, creating the necessary infrastructure for large-scale agriculture, and establishing new farms.

Bradfield *et al*. (2016), in their analysis of Pakistan's agricultural sector using the SWOT method, concluded that despite the sector's importance due to its significant share in the country's gross domestic product (GDP) and the available capabilities, agricultural development in Pakistan faces serious weaknesses and threats. The research suggests government intervention to increase productivity, provide farmer training, and offer loans to small farmers. Goldstein *et al.* (2012) published a report on the project "Investment Scenarios for the US Hawaii Region," aimed at assisting in the design of a land use map for the northern Ohio coastal region, with a focus on the agricultural sector. The project identified key development variables and, using the Delphi method and consultative workshops with regional stakeholders, formulated possible scenarios for the Hawaii region. Their research found that the key influential variables for the future use of the area were the land irrigation system and the future land sales strategy. Gavetti & Menon (2016) conducted a major project on the future of food and agriculture, using scenario writing methods. They identified the sector's most important challenges, including regulating demand and supply for agricultural products, addressing food system instability, ending hunger, and preserving biodiversity and ecosystem stability while feeding the global population. After identifying these challenges, they pinpointed the key factors to address them and suggested tools for better policymaking for the future. Abdollahi *et al.* (2020), in their research titled "Analysis of the Key Drivers of the Development of the Poultry Industry Using a Forward-Looking Approach," identified three key drivers for the development of the poultry industry. These include macroeconomic and commercial policies aligned with the development and formation of a market based on innovation, an educational system focused on fostering a culture of innovation, and access to loans and financial resources. Takallo *et al.* (2020) discussed the future development of human resources in the agricultural sector in the rural areas of the central part of Malair city. The research identified 24 key factors in human resource development. Among these, the most significant drivers for future development were integrated management of rural development, sustainable employment, advanced technology, the elimination of discrimination between urban and rural areas, and the expansion of production cooperatives. Based on these factors, the study proposed three groups of scenarios for the future of human resources in the agricultural sector of rural areas. Bagheri *et al*. (2020) investigated the future research of the Agricultural Engineering and Technical Research Institute for the horizon of 1404. The

results showed that self-sufficiency in the production of basic products, the impact of product quality and health indicators on pricing, the contribution of the research budget to national gross production, and the adoption of new technologies by users were the most influential drivers. Additionally, the study identified 9 economic drivers, 10 policy and planning-related factors, 7 science and technology drivers, 6 environmental factors, 3 cultural-social factors, and 5 human resource leadership factors. The political and planning agents, along with the economic agent, were identified as having the most significant influence on the future of the institution. In their research, Beheshti et al. (2020) studied and investigated water resource management scenarios using a future-research approach in Tabriz city. According to the results, 15 key factors were identified as influencing the state of water resources in Tabriz. Among the most important and influential factors in water resource management were climate change, water quality, the economic productivity of water, investment in the supply sector, consumption and water infrastructure, as well as changes in precipitation and cropping patterns. Ghoochani *et al*. (2019) conducted research entitled "Macro-Inspection of Drivers of Water Resources Management in the Agricultural Sector of Iran." The study identified four main drivers that are highly effective and important in the field of agricultural water management. These drivers include: 1) institution building in the field of agricultural water management, 2) the establishment of an integrated management system for water resources in catchment areas, 3) the management of the country's water resource conflicts, and 4) the volume delivery capacity of agricultural water.

Jashari & Moradi (2019) developed a scenario and strategy for the agricultural sector's development by identifying key drivers in the rural areas of Sistan and Baluchistan province. Among these drivers, the most influential include: improving agricultural knowledge, managing water resources effectively, financing agricultural projects, developing transformation industries in agriculture, and enhancing marketing knowledge for agricultural products. Nikanfar & Naseri (2019), in their research titled "Future Study of Energy Efficiency in Wheat Production on the Eastern Margin of Lake Urmia," concluded that from an energy perspective, the conservation tillage system is preferred over conventional tillage for wheat production. However, in many cases, the statistical difference in energy parameters between the two systems was not significant. The study suggests that proper implementation of conservation tillage with the right tools and equipment can improve energy parameters in wheat production. The Research Center of Majlis (2018) also examined the future of agriculture in Iran, finding that agricultural production is unlikely to meet the growing demand in the future. Over the past decade, the average annual growth rate of agricultural production has been 2.63%, while demand for agricultural products has grown at an average rate of 4.13% annually. Sadeghi & Khanzadeh (2019) analyzed the strategic development of agriculture in the Urmia Lake catchment area using the SWOT method and the QSPM matrix. The research showed that the primary strategy for the region's agricultural development is a defensive strategy, with the top priorities for implementing sustainable development programs being: managing water consumption in agriculture, developing agricultural mechanization, integrating agricultural lands, and improving the literacy and awareness of human resources working in agriculture. Sustainable agriculture is seen as the key solution to the crisis. Ahmad & Enayatollah (2013) in their study titled "Challenges of Agricultural Development in Iran" identified several key challenges facing agriculture in the country, including: limited access to water, declining water levels in the Caspian Sea, the conversion of agricultural land for non-agricultural purposes, land shortages, insufficient government support, organizational inefficiencies, increasing water salinity, the influence of political issues on decision-making, unplanned land use systems, lack of

advanced technological infrastructure, and unfavorable social and economic conditions.

Eghbali (2020) examined the water governance system in the Zayandeh River basin to promote sustainability of water resources. The research highlighted that the most influential factors in the water governance system included the Supreme Water Council and the subordinate organizations of the Ministry of Energy. Key legal challenges identified were unclear ownership rights, the non-participation of stakeholders in water legislation and management, and weaknesses in existing laws. Enteshari & Safavi (2019) investigated the administrative-institutional system of water management in the Zayandeh-Rood watershed using a qualitative grounded theory method. They identified factors such as incomplete and inaccurate information, differing understandings of issues, ineffective meetings, conflicts of interest, lack of coordination between organizations, potential corruption, and weak supervision as contributing to the ineffectiveness of the current administrative structure. Hatami & Noorbakhsh (2019) focused on the semantic reconstruction of the water crisis in the eastern region of Isfahan based on contextual theory. They extracted the core category of "mismanagement of water" and found that, according to farmers, the current water crisis was directly related to mismanagement. This mismanagement has manifested itself in governance practices that exclude social stakeholders. Mahmoodi & Karimi (2015) conducted a case study of agricultural land use changes in the Zayandeh River basin in Isfahan province. Their research showed an increasing trend in the conversion of agricultural land to residential land, with the area of residential land growing from 14,000 hectares to 39,000 hectares over the study period. This change has had significant effects on the components of sustainable development, which can be categorized into environmental, economic, social, and agricultural impacts.

Given the limited research in the field of agriculture with a future research approach, the studies emphasize the potential benefits of future research in identifying key factors and guiding planning for agriculture. With proper planning and a focus on the future, these studies can significantly contribute to sustainable agricultural development. The present research aims to identify scenarios for sustainable agricultural development in the Zayandeh River catchment area in Isfahan province.

Research Method

The current research is applied in nature and employs a descriptive-survey methodology, as it describes and interprets existing conditions, relationships, common ideas, and ongoing processes. In terms of data type, this research is both quantitative and qualitative. The statistical population for this study includes: 1) managers and entrepreneurs in the agricultural sector within the Zayandeh River watershed in Isfahan province, 2) academic researchers and professors involved in the agricultural sector in the same region, and 3) policymakers and managers engaged in the planning and policymaking process for agricultural development in the Zayandeh River watershed. Participants were selected using a non-probability snowball sampling method. Data were collected using a combination of library resources, researcher-developed questionnaires, and interviews. Qualitative data were gathered through open-ended questionnaires and interviews with experts, as well as document analysis. Quantitative data were compiled numerically and obtained through the weighting of Delphi questionnaires. To identify the factors affecting agricultural development, five experts were interviewed. To validate these factors, the identified variables were then presented to 25 experts in the form of a researcher-made questionnaire to assess the importance of each factor. To ensure the validity of the research instruments, form-content validity was employed. The questionnaire, along with the research questions, was shared with several experts, including the supervisor, who were asked to evaluate its suitability for measuring the research variables.

Reliability was assessed using Cronbach's alpha and the composite reliability coefficient

to check the internal consistency of the questionnaire. Given that the Cronbach's alpha value for the variables was 0.944, the reliability of the instrument was confirmed. A matrix with dimensions of 8x8 was used for the scenario planning part of sustainable agricultural development using the results of interviews with experts and a Delphi questionnaire and was given to the experts of the agricultural sector. In the following, in order to enter these elements into the Scenario Wizard software environment, the related subcategories of each were defined with their own unique statuses in the software environment. Then, by expressing the possible states for each of these factors, the matrix of cross-effect analysis was formed and the statistical sample was asked to rate them according to the effect of one factor on other related factors from -3 to +3 in the framework of the formed matrix. (-3: Strongly negative effect; -2: Relatively negative effect; -1: Limited and weak negative effect; 0: Neutral effect; +1: Weak positive effect; +2: Moderate positive effect; +3: Strong positive effect).

The scenario wizard software does not emphasize that the scenarios are selected from different ranges and they are designed only based on negative and positive relationships. Scenario planning is still a more or less new method that has been developed in various ways. Diversity of thought in the field of scenario planning is a kind of capital because it has led to a diverse set of interpretations in scenario programming. In fact, scenarios, Jammayeh and Shah Bayt are futuristic activities that draw alternative images of believable futures in the field in question. A scenario is a narrative with possible outcomes and effective links that connect the future state with the present; while also describing key decisions, events and consequences throughout her narrative (Nematollahi, et al, 2016). In fact, the scenario describes a situation in the future and a path that takes us from the present to this future; therefore, the process of planning with the help of scenario or scenario planning helps us to understand the bigger space of the future.

It should be noted that Zayandeh Rood catchment is the second catchment of the Central Plateau, which is coded with number 42. This basin is located in the middle part of the central plateau, its area is 41550 square kilometers. There are 21 study areas in this watershed, 17 of which are (Kupa Segzi, Barkhar Isfahan, Morche Khort, Alavijah and Dehgh, Mimeh, Najaf Abad, Karon, Mehyar Shamli, Lanjan, Chadegan, Boyin-Miandasht, Chehlkhaneh, Daran- Domain, Shahreza, South Mehyar, Esfandaran, Gavkhoni Lagoon) under the management of Isfahan Regional Water Company and three units (Chalgerd - Qala Shahrokh, Yanchashme and Ben - Saman) under the coverage and supervision of the Regional Water Company of Chahar Mahal and Bakhtiari Province and another unit (Izdkhas) is under the supervision of Fars Regional Water Company. About 87.7% of the catchment area of Zayandeh River is located in Isfahan province, which is of considerable importance for consumption in the agricultural and drinking sectors of Isfahan province, in such a way that between the years 2015-2015, water from the Zayandeh Rood basin was used to irrigate 331,220 hectares of agricultural land. And the amount of exploitation of underground water resources for consumption in the agricultural sector between 1399-1400 has been reported as 3200 million cubic meters. Also, the amount of exploitation of surface water resources for consumption in the agricultural sector between 2018-2019 was reported to be 1.544 million cubic meters. Therefore, careful planning to manage water consumption in Zayandeh Rood basin is inevitable.

Findings and Discussion

Descriptive findings showed that in terms of education, the majority of them (12 people) had a master's degree and in terms of gender, 100% of them were men, and in terms of history of participation in policy-making activities, the majority of the respondents did not participate. Also, the majority of the respondents did not have teaching experience at the university (Table 1).

Table 1- Demographic characteristics of experts

History of participation in policy activities		University lecturer		Gender		Education			Total number of respondents people
No	Yes	No	Yes	Woman	Man	Ph.D	senior expert	expert	
14	11	16	9	0	25	8	12	5	25

As stated earlier in the research method section, an 8x8 matrix was extracted through interviews with experts and was given to the experts of the agricultural sector. The results of the expertise index show that the experts have more than 50% expertise in all the questions raised and they have high knowledge about the subject. Also, the desirability index shows that there is a lot of desirability regarding one of the two situations raised in the questionnaire questions and in this regard, agriculture in a controlled environment with -0.68% has the highest percentage and changing the country's education system with -0.43% has the lowest level of favorability. The consensus index also indicates the level of uncertainty associated with each option. It shows that the development of new programs in the entrepreneurship sector, changes to the country's education system, and strengthening land use laws exhibit the highest levels of uncertainty. Among the issues raised, changing the cultivation pattern and focusing on the production of low-water-demanding crops emerges as the most crucial factor for the sustainable development of the agricultural sector in the future (Table 2).

In order to enter these elements into the Scenario Wizard software environment, these 8 factors were defined with their unique status in the software environment. Then, by expressing the possible states for each of these factors, the matrix of cross-effect analysis was formed and the statistical sample was asked to rate them according to the effect of one factor on other related factors from -3 to +3 in the framework of the formed matrix. In Table 3, drivers and possible influencing modes of sustainable agricultural development in Zayandeh River watershed of Isfahan province are presented.

Table 2- The results of experts' answers to Delphi questionnaire questions

Row	Question	Expertise index	Desirability index	Consensus index	Significance index
1	Farming in open space or controlled	73.61	-0.68	-0.44	84.25
2	Strengthening the current cultivation pattern or changing the cultivation pattern and production of low water-demanding crops	68.85	-0.65	-0.68	85.61
3	Direct government rule or popular participation	69.69	0.51	0.49	73.32
4	Traditional agriculture or smart agriculture	65.6	-0.61	0.68	77.84
5	Strengthening current consumption management or modifying consumption pattern	62.7	-0.59	-0.58	78.82
6	Development of current actions in the entrepreneurship sector or development of new programs in the entrepreneurship sector	70.13	-0.65	-0.28	74.75
7	Strengthening the education system of the country or changing the education system	65.15	-0.43	0.18	71.98
8	Removing agricultural land use rules or strengthening the rules	75.31	-0.53	-0.13	76.62

Table 3- The main factors and possible situations facing the sustainable development of agriculture in the catchment area of Zayandeh River in Isfahan province

Acronym	Possible situation	Degree of desirability	The main influencing factors
A1	Elimination and reduction of government support	Critical	Government support and financial facilities in the agricultural entrepreneurship sector
A2	Maintaining and continuing the current trend	Static	
A3	Increasing government support	Desirable	
F1	Lack of development of low water-demanding products such as medicinal plants, saffron and saffron	Critical	Development of low water-demanding products such as medicinal plants, saffron and saffron
F2	Maintaining the current situation of using low water-demanding products such as medicinal plants, saffron and saffron	Static	
F3	Development of low water-demanding products such as medicinal plants, saffron and saffron	Desirable	
B1	Lack of agricultural development in controlled environments such as greenhouses	Critical	Development of agriculture in controlled environments such as greenhouses
B2	Continuing the current trend of farming in controlled environments such as greenhouses	Static	
B3	Increasing the development of agriculture in controlled environments such as greenhouses	Desirable	
U1	Reducing the economic productivity of water	Critical	Increasing the economic productivity of water
U2	Continuation of the current trend of economic water efficiency	Static	
U3	Increasing the economic productivity of water	Desirable	
S			
S1	Deterioration of water management between industry and agriculture sectors	Critical	Proper management of water consumption between industry and agriculture sectors
S2	Continuation of the current process of water consumption management between industry and agriculture sector	Static	
S3	Improving water consumption management between industry and agriculture sectors	Desirable	
L			
L1	Reduction of employment in the agricultural sector	Critical	Development of employment fields in the agricultural sector
L2	Continuing the current trend of employment in the agricultural sector	Static	
L3	Increasing employment in the agricultural sector	Desirable	
H			
H1	Reduction in the production of export products	Critical	Development of export products
H2	Continuing the current trend of producing export products	Static	
H3	Increasing the production of export products	Desirable	
G			
G1	Worsening management of cropping pattern	Critical	Proper management of cropping pattern
G2	Continuing the current trend of cropping pattern management	Static	
G3	Improving the management of the cultivation pattern	Desirable	

Finally, according to the effect of one factor on other related factors, 5 believable scenarios were identified by considering possible situations resulting from key factors and their commonalities or differences in the categories of favorable, static and critical scenarios (Table 4).

The percentages and number of scenarios in Table 5 show the distribution of different situations. Specifically, critical situations account for 20 scenarios, static situations (maintaining the current state and continuing the existing trend) for 12 scenarios, and favorable situations for 8 scenarios,

representing the highest to lowest amounts, respectively. In other words, 50% of the scenarios are related to critical situations, 30% to static situations, and nearly 20% to favorable situations, as explained below.

Table 4- The status of each of the factors according to optimal to critical status

The fifth scenario	The fourth scenario	The third scenario	The second scenario	The first scenario	scenarios/ Agents
Desirable	Static/Continuation of current trend	Undesirable	Static/Continuation of current trend	Undesirable	Government financial support and facilities in the field of agricultural entrepreneurship
Desirable	Static/Continuation of current trend	Undesirable	Static/Continuation of current trend	Undesirable	Development of areas to increase employment in the agricultural sector
Desirable	Static/Continuation of current trend	Static/Continuation of current trend	Static/Continuation of current trend	Static/Continuation of current trend	Development of low water-demanding products
Desirable	Static/Continuation of current trend	Static/Continuation of current trend	Undesirable	Undesirable	Agricultural development in controlled environment such as greenhouses
Desirable	Undesirable	Undesirable	Undesirable	Undesirable	Correct management of water consumption between industry and agriculture sectors
Desirable	Static/Continuation of current trend	Static/Continuation of current trend	Undesirable	Undesirable	Increasing the economic productivity of water
Desirable	Undesirable	Undesirable	Undesirable	Undesirable	Development of export products
Desirable	Undesirable	Undesirable	Undesirable	Undesirable	Correct management of the cultivation pattern

Table 5- Number and percentage of situations

Percentage	Number	Status
20	8	Desirable
30	12	Static
50	20	Critical
100	**40**	Total

Favorable scenarios

According to favorable, static and critical situations; Scenario number 5 is a favorable scenario. In this scenario, all states of agents are favorable. In total, these scenarios have 8 favorable situations, which are shown in Table 6.

Static scenarios

According to favorable, static and critical situations; Scenario number 4 is a static scenario. In this scenario, there are 5 static states, 3 unfavorable states, which are shown in Table 7.

Table 6- Characteristics of desirable scenarios

General features	Number of scenarios	Category
Increasing government support The trend of increasing employment in the agricultural sector The process of increasing agriculture in a controlled environment Improving water consumption management between industry and agriculture sectors The increasing trend of producing low water-demanding products Increasing the economic productivity of water Increasing the production of export products Improvement of cultivation pattern management	**Fifth**	Desirable

Table 7- Characteristics of static scenarios

General features	Number of scenarios	Category
Maintaining and continuing the current process of government support and financial facilities in the agricultural entrepreneurship Continuing the current trend of employment in the agricultural sector Maintaining and continuing the current trend of cultivating low water-demanding crops such as saffron Maintaining and continuing the current trend of agriculture in controlled environments Deterioration of water consumption management between industry and agriculture sectors Maintaining and continuing the current trend of economic water efficiency Reducing the cultivation of export products Worsening of proper management of cropping pattern	**Fourth**	Static

Critical Scenarios

According to favorable, static and critical situations; Scenarios number 1 to 3 are critical scenarios. From the total of 24 situations in these scenarios; 17 critical situations 7 situations have a static situation and maintain the existing situation, which is shown in Table 8.

Based on the results of Table 9, the fifth scenario with 8 favorable assumptions (100 percent) is the most favorable situation and the first scenario with 7 critical assumptions (87.5 percent) is the most unfavorable situation for the catchment area.

Table 8- Characteristics of critical scenarios

General features	Number of scenarios	Category
Removal and reduction of government support Deterioration of water supply and consumption Continuing the current trend of government support and facilities in the agricultural entrepreneurship sector Continuing the current trend of employment in the agricultural sector Continuation of the current trend of cultivation of low water-demanding crops The decreasing trend of growing crops in a controlled environment Deterioration of proper management of water use between agriculture and industry Continuation of the process of economic efficiency of water The trend of reducing the cultivation of export crops Worsening of proper management of cropping pattern	**First to third**	Critical (unfavorable(

Table 9- Coefficients, number and percentage of each situation separately for each scenario based on the triple spectrum

Critical situations									Adverse situations	Status coefficients	The number of statuses separately	scenario
Percentage of critical conditions	Maximum critical conditions	The extent of critical conditions	Percentage of desirability	Ideal score	The desired amount	3-	1	3	critical	static	Desirable	
87/5	-24	-21	0	24	0	21-	1	0	7	1	0	1
62/5	-24	-15	0	24	0	15-	3	0	5	3	0	2
62/5	-24	-15	0	24	0	15-	3	0	5	3	0	3
37/5	-24	-9	0	24	0	-9	5	0	3	5	0	4
0	-24	0	100	24	24	0	0	24	0	0	8	5

Table 10- Possible scenarios of sustainable agricultural development

The fifth scenario	The first scenario	scenarios/ Agents
Increasing government support	Removal and reduction of government support	Government financial support and facilities in the field of agricultural entrepreneurship
Increasing employment in the agricultural sector	Reduction of employment in the agricultural sector	Development of employment fields in the agricultural sector
Increasing the cultivation of low water-demanding crops	Continuation of the current trend of growing low water-demanding crops	Development of cultivation of low water-demanding crops
Increasing cultivation in controlled environments	Reduction of cultivation in controlled environments	Agricultural development in a controlled environment
Improving water consumption management between industry and agriculture sectors	Deterioration of water consumption management between industry and agriculture sectors	Correct management of water consumption between industry and agriculture sectors
Increasing the economic productivity of water	Reducing the economic productivity of water	Increasing the economic productivity of water
Increasing the production of export products	Reducing the production of export products	Development of export products
Improvement of cultivation pattern management	Deterioration of management of cultivation pattern	Correct management of the cultivation pattern

Identify Possible Scenarios

Among the 5 believable scenarios and software outputs and according to their total impact score, which are between 85 and 109; 2 scenarios are the most likely scenarios. These scenarios have a total effect score of 87 to 109, of which 1 is favorable and 1 is critical. Which is shown in Table 10.

Conclusions and Suggestions

The complexity of human changes and variables, coupled with the unpredictable nature of environmental and global economic factors affecting agricultural activities, presents significant challenges for sustainable agricultural development. On one hand, the strategic importance of food security and combating poverty is critical, while on the other, the continuous and rapid changes make traditional planning methods inadequate. The increasing uncertainties and the emergence of unexpected events have created a situation where planning has become increasingly difficult. Therefore, it is necessary that the developed strategies to face these issues are based on comprehensive and optimal analysis which examines the main dimensions of agriculture and food sector in an integrated way. Therefore, this research was conducted with the aim of developing possible scenarios of sustainable agricultural development in the Zayandeh River watershed in Isfahan province. The results of Delphi analysis showed that experts in agriculture in controlled environment have the highest percentage of favorability with -0.68%. Since sustainable production is the most important task in agriculture Therefore, in sustainable production, agricultural products needed by the society should be produced to the extent that the relative advantage of each province allows and the biggest obstacle in this path is the water problem. Given that agriculture faces numerous challenges such as climate change, fluctuating agricultural product markets, and political decisions, it is crucial to develop a strategic plan to stabilize some of these variables while optimizing production based on others. One approach to achieving this is through farming in controlled environments, such as greenhouses, which allow for better control of factors like water consumption, ultimately increasing production. Additionally, among the various issues raised, changing cultivation patterns to focus on low-water-demanding crops is considered the most important for the sustainable development of the agricultural sector in the future. Since agriculture is the largest consumer of water, improving water consumption management and enhancing efficiency in this sector can significantly reduce water usage. One of the methods that improves the management of

water consumption and ultimately increases the efficiency of water consumption, drought risk management of agriculture in dry areas and determining the optimal pattern of low water intensive cultivation. Research was conducted by Joolaei (2004) in the field of investigating cultivation patterns, the results indicate that the implementation and design of the optimal cultivation model in the form of a specific program has been used in many countries of the world and with its help, many problems of crop and garden production have been solved and to determine the optimal pattern of cultivation in each region, micro and macro goals should be considered.

The findings of the scenario wizard analysis showed that there are 5 believable scenarios based on the effect of one factor on other related factors. Finally, among the 5 believable scenarios and the outputs of the software and according to the total score of their effects, 2 scenarios are the most probable scenarios that among them, 1 favorable scenario and 1 critical scenario. Therefore, according to these results, supporting the agricultural sector for various reasons, including creating employment and booming production in the former and latter industries, establishing food security, the essentiality of some agricultural products in the community's food basket, rural development and maintaining the structure of the rural population and preventing migration to cities, preservation and sustainability of the environment, contribution to national security and independence of the country, creation of added value and increase of national income through non-oil exports, the requirements of relative and structural advantage of production and self-sufficiency and raising the income of farmers are accepted. Therefore, in all developed and developing countries, producers support the agricultural sector in various ways. Hatberg (2000) who studied the effects of Sweden's support policies in agricultural development concluded that due to the effectiveness of these policies, political reforms should also be carried out and in order to meet the needs of farmers, financial resources should be available to them.

There are various tools to support the agricultural sector, the use of each of which has different effects on the agricultural sector and other economic sectors. In general, agricultural policy in Iran can be divided into three categories: pricing policy, institutional support, and other support. One of the important policies in the economy that is carried out in most countries is to support the producer or consumer through the payment of subsidies. Statistics also show that only 12% of Iran's area is under cultivation, more than 90% of the consumed water is allocated to the agricultural sector, and part of it is wasted. Meanwhile, the average efficiency of water consumption in the agricultural sector in Iran is 40% lower than the average of the world standard. Therefore, due to the limited and fixed amount of renewable water, the competition between drinking, agricultural and industrial water users on the one hand and the competition at the catchment level on the other hand can intensify in the future or cause new challenges. On the other hand, water pollution has spread and during periods of drought and uneven distribution of rainfall on the ground and destructive works, flowing water caused by floods has created conditions that if water resources are not managed and their quality and quantity should not be considered it may cause unpredictable tensions for countries. Therefore, in order to prevent this crisis, the first step is to create a correct and rational culture of water consumption and improve it through the formulation of optimal water consumption, planning and implementation of water consumption management plans in agriculture and modification of tariffs for high consumption subscribers and implementation of incentive plans such as correct subsidies in the direction of developing modern irrigation plans. New technology and applying new methods can help us in this goal of providing enough water but it will not be able to be together forever. The best solutions to promote the culture of correct and optimal water consumption in the agricultural sector require a correct and reliable cultural infrastructure and culture building in the agricultural society. In

this context, both government and non-government sectors, which include farmers and specialists in this sector, must be aware of their duties and act and have continuous communication and coordination in the development of agriculture and especially water and just like in the field of crop cultivation, land preparation plans are made in this section, the national study of water resources and the balance of the region should be compiled and implemented that this is not possible without promoting and educating and informing farmers by the government and the relevant ministry of research and education and creating a culture to save agricultural water consumption is not possible only by a ministry or government body and there is a need for national and coherent determination on the part of all governmental and non-governmental institutions. Due to the large consumption of water in the agricultural sector, water demand management, especially the management of exploitation and improvement of the economic efficiency of water and considering the water input as an economic and valuable commodity, is of special importance in the country. Economists to solve the problem of food production from limited water resources and prevent excessive import of agricultural products, they recommend increasing the physical productivity and economic productivity of water (Heydari, 2013). In developing countries, improving agricultural water productivity is considered one of the most important basic solutions. Finally, according to the results obtained from the research, the following suggestions can be made.

- Changing the traditional irrigation pattern and developing the cultivation of low water-demanding plants such as saffron, saffron and medicinal plants using modern scientific methods of irrigation.

- Reducing the amount of water consumption in the agricultural sector by changing the cultivation pattern and increasing the economic efficiency of water.

- Implementing a model for crop cultivation, based on the country's macro policies, market structure, farmers' knowledge and regional and climatic potentials in order to preserve the environment and achieve sustainable economic advantages.

- Introduction of potential fields by relevant organizations such as agricultural jihad, where ideas in those fields have the ability to be commercialized and successful in order to guide and organize talents and innovations in the agricultural sector.

- Applying appropriate policies from the government in the field of obtaining facilities, exporting agricultural products, security for investment in the agricultural sector, product insurance, strengthening the production sectors, making the market of agricultural products competitive and paying attention to fostering the spirit of creativity and innovation among students.

- Cultivation and promotion of correct and optimal use of water, implementation of incentive schemes by government agencies such as paying correct subsidies to new and established irrigation schemes and modifying tariffs for high-consumption subscribers.

- Using modern and smart agricultural methods, including remote sensing methods, information technology, nano technology and agricultural applications to increase the economic efficiency of water in the agricultural sector.

References

1. Ahmad, U., & Inayatullah, M. (2013). Challenges to the agricultural development in Iran. *International Journal of Innovative Research & Development, 2*(10), 85-91.
2. Ajilore, O., & Fatunbi, O.A. (2018). Exploring the futures of agricultural research and innovations (ARI) systems in Africa. *Journal of Futures Studies, September, 23*(1), 23–36. https://doi.org/10.6531/JFS.201809_23(1).0003
3. Akrami, M., Mahdavi, R., Rezaie, M., Vagharfard, H., & Barkhordari, J. (2021). Calculating the water requirement and providing a pattern of horticultural cultivation with low water demand

and compatible with dry areas, in order to reduce the vulnerability of agricultural drought) Case study: Pishkoh watershed, Yazd province. *Scientific Research Journal of Irrigation and Water Engineering, 12*(46), 314-337.

4. Asadi, H., Mahmoodi, M., & Zare, SH. (2021). Determining the profitability and economi efficiency of agricultural water in the production of crops. *Iran Irrigation and Drainage Journal, 6*(15), 1404-1411.
5. Bagheri, N., Keshavarz, M., Abbasi, F., Abbasi, N., & Bordbar, M. (2020). Future research of the agricultural engineering and technical research institute in the horizon of 1404. *Journal of Strategic Research in Agricultural Sciences and Natural Resources, 5*(1), 1-18. https://doi.org/10.22047/SRJASNR.2020.113048
6. Bahrami, M., Asadi, M., & Khaliliyan, S. (2020). Evaluation of water efficiency indicators with an emphasis on modern and traditional irrigation in crops of Shahryar city. *Environment and Water Engineering, 6*(3), 284-292.
7. Beheshti, M., Behboodi, D., Zali, N., & Ahmadzadeh, F. (2019). Scenarios of water resources management based on future research approach (case study: Tabriz city). *Two Quarterly Journals of Iranian Future Studies,* 5(2), 203-228. https://doi.org/10.30479/JFS.2020.12446.1150
8. Bradfield, R., Derbyshire, J., & Wright, G. (2016). The critical role of history in scenario thinking: augmenting causal analysis within the intuitive logics scenario development methodology. *Futures, 77,* 56-66. https://doi.org/10.1016/j.futures.2016.02.002
9. Eghbali, J. (2020). Analysis of water governance system in Zayandeh Rood catchment area in the direction of stabilization of agricultural water resources. Department of Agricultural Development, Faculty of Agriculture and Natural Resources, University of Tehran .
10. Enteshari, C., & Safavi, H. (2019). Investigating the administrative-institutional system of water management in the Zayandeh River basin using the qualitative method of grounded theory. *Water and Wastewater Journal, 30*(6), 1-17. https://doi.org/10.22093/WWJ.2019.149029.2749
11. Fakai Sordeie, B., Shahnooshi, N., & Mohammadi, H. (2020). The future research of Iranian wheat. *Journal of Agricultural Economy, 14*(1), 27-49. https://doi.org/10.22034/IAES.2020.124268.1761
12. Gavetti, G., & Menon, A. (2016). Evolution cum agency: Toward a model of strategic foresight. *Strategy Science, 1*(3), 207-233. https://doi.org/10.1287/stsc.2016.0018
13. Ghoochani, A., Dabiry, D., & Ghaniyan, M. (2019). Macro survey of drivers of water resources management in Iran's agricultural sector. *Scientific Research Quarterly of Public Policy, 5*(2), 59-78. https://doi.org/10.22059/PPOLICY.2019.72272
14. Goldstein, J., Caldarone, G., Duarte, K., Hannahs, N., & Mckenzie, E. (2012). Invest Scenarios case study: Hawaii, USA. WWF, Morges.
15. Gutzler, C., Helming, K., Balla, D., Dannowski, R., & Paol, C. (2015). Agricultural land use changes–a scenario-based sustainability impactassessment for Brandenburg, Germany. *Ecological Indicators, 6*(48), 505-517.
16. Hatami, A., & Noorbakhsh, S. (2018). Reconstructing the meaning of the water crisis in the east of Isfahan based on grounded theory. *Journal of Applied Sociology, 30*(73), 122-143. https://doi.org/10.22108/JAS.2018.109357.1299
17. Heidari, N. (2014). Determining and evaluating the efficiency of water consumption of some major crops under the management of farmers in Iran. *Journal of Water and Irrigation Management, 1*(2), 43-57.
18. Holtsberg, C. (2000). Swedish Support to Agricultural Development. Natural Resources Managemen Division, SIDA.
19. Jashari, S., & Moradi, A. (2018). Developing strategies for the development of agricultural economy in the rural areas of Sistan and Baluchistan province with a future research approach.

Space Economy and Rural Development Quarterly, 8(29), 51-66.

20. Jashari, S., & Moradi, A. (2017). An analysis of the development drivers of the agricultural sector of Sistan and Baluchistan province with the principles of future research. National conference of economy, development management and entrepreneurship with the approach of supporting Iranian goods. May 11, Zahdan. EDME01_108
21. Joolaei, R. (2004) Management of crop pattern in 3central counties of Fars province in a multi-region.
22. Keramatzadeh, A. (2006). Comparative study of characteristics and methodologies of social sciences and natural sciences from Popper's point of view. *Field and University Magazine, 12*(48), 28-48.
23. Mahmoodi, A., & Karimi, H. (2015). Economic valuation of water for large and small wheat farms: a case study of Tabas city. *Journal of Agricultural Economics and Development, 25*(100), 1-19.
24. Majlis Research Center. (2018). Foresight of the agricultural sector: environmental survey, supply and demand. Vice President of Infrastructure Research and Production Affairs, Infrastructure Studies Office.
25. Makal, A., Banerjee, A., Roy, A., Hazra, S., & Polley, K. (2017). Issues and problems in agricultural development: A study on the farmers of West Bengal. Bhui, S., Das, M. S. and Coomar, P. C. Development among the Tribal and Minority Societies. Publisher: Gyan Publishing House, New Delhi, 179-182.
26. Nematollahi, Z., Fakoori, N., Shahpoori, A., & Ashktorap, N. (2016). Are government support policies effective on Iran's agricultural growth? 10th Biennial Conference on Agricultural Economics of Iran, Scientific Association of Agricultural Economics of Iran, Shahid Bahonar University of Kerman, 237-245.
27. Nikanfar, R., & Naseri, A. (2019). Future research of energy efficiency in water wheat production in the eastern margin of Lake Urmia. *Environmental Science Quarterly, 17*(2), 80- https://doi.org/101. 10.29252/ENVS.17.2.81
28. Nsikak- Abasi, A.E., & Kesit, K.N. (2015). Barriers to increasing agricultural production in Nigeria. *American Journal of Agricultural Science, 2*(4), 138-143.
29. Sadeghi, H., & Khanzadeh, M. (2019). Strategic analysis of agricultural sector development using swot method and Qspm matrix: a case study of Urmia Lake catchment area. *Agricultural Economics and Development, 27*(108), 87-118. https://doi.org/10.30490/AEAD.2020.252675.0
30. Sharifzadeh, A., & Hosseini, M. (2009). Necessity and fields of application of future research in the promotion and sustainable development of agriculture. The 3rd Congress of Science and Promotion of Agricultural Education, March 10, Mashhad.
31. Takallo, A., SHamsoddini, A., Rahmani, B., & Valishariatpanahi, M. (2019). Future research of human resources development in the agricultural sector in rural areas (Case: Central part of Malair city). *Scientific and Research Quarterly of the Iranian Geographical Society, 18*(67), 103-88.
32. Zali, N., & Atriyan, F. (2016). Development of regional tourism development scenarios based on the principles of future research (case study of Hamadan province). *Amish Sarmeen, 8*(1), 107-131. https://doi.org/10.22059/JTCP.2016.59147

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مقاله پژوهشی

جلد ۳۸، شماره ۴، زمستان، ۱۴۰۳، ص. ۴۲۹-۴۱۳

تدوین سناریوهای توسعه پایدار کشاورزی در حوضه آبریز زاینده رود استان اصفهان

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تاریخ دریافت: ۱۴۰۳/۰۷/۰۲

تاریخ پذیرش: ۱۴۰۳/۰۸/۲۷

چکیده

بخش کشاورزی در کشورهای در حال توسعه نقش مهمی را در پیشبرد توسعه ملی ایفا می‌نماید و سیاستگذاری عقلایی و برنامه‌ریزی راهبردی جهت پیشبرد توسعه پایدار این بخش یکی از دغدغه‌های اصلی کنشگران نهادی ذیربط به شمار می‌رود. در این راستا پژوهش حاضر با هدف شناسایی سناریوهای توسعه پایدار کشاورزی در حوضه آبریز زاینده رود استان اصفهان انجام گرفت. پژوهش حاضر کاربردی، از نوع توصیفی-پیمایشی بود. جامعه آماری خبرگان مرتبط با توسعه کشاورزی در استان بودند. جهت جمع‌آوری داده‌ها از منابع کتابخانه ای، پرسشنامه و مصاحبه استفاده گردید. برای شناسایی مؤلفه‌ها و پیشران‌های اولیه مؤثر بر توسعه پایدار کشاورزی در حوضه آبریز زاینده رود استان اصفهان از روش دلفی و مصاحبه با نخبگان و مسئولین اجرایی استفاده شد و برای انتخاب خبرگان نیز تکنیک گلوله برفی به کار رفت. در نهایت تعداد ۸ پیشران کلیدی در راستای تبیین متغیرهای پژوهش در قالبی استراتژیک مورد شناسایی و تفکیک قرار گرفتند. بر این اساس در قسمت مربوط به بیان اولویت‌های پژوهش در دو حالت مستقیم و غیرمستقیم، این ۸ عامل کلیدی در اولویت‌های مختلف تکرار شده اند. پرسشنامه‌ها بین ۲۵ نفر از خبرگان توزیع گردید. در این پژوهش برای آینده نگاری توسعه پایدار کشاورزی ۵ سناریوی باورکردنی با درنظر گرفتن وضعیت‌های حاصل از عوامل کلیدی و وجه اشتراک و یا تفاوت‌های آنها در دسته‌های سناریوهای مطلوب، ایستا و بحرانی شناسایی و با توجه به نمره کل اثر آنها که بین ۸۵ تا ۱۰۹ هستند؛ تعداد ۲ سناریو محتمل‌ترین سناریوها تشخیص داده شد که یک سناریو مطلوب و یک سناریو بحرانی هستند.

واژه‌های کلیدی: آینده‌نگاری، توسعه کشاورزی، حوضه آبریز زاینده رود، سناریو نگاری

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https://doi.org/10.22067/jead.2024.89627.1292

Journal of Agricultural Economics & Development

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

Research Article
Vol. 38, No. 4, Winter 2025, p. 431-442

Assessing the Competitiveness and Policy Impact on Broiler Production in Kurdistan Province, Iran: A Policy Analysis Matrix Approach

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Received: 08-11-2024
Revised: 10-12-2024
Accepted: 28-12-2024
Available Online: 28-12-2024

How to cite this article:
Haji-Rahimi, M., Alizadeh, P., & Sharifi, F. (2025). Assessing the competitiveness and policy impact on broiler production in Kurdistan province, Iran: A policy analysis matrix approach. *Journal of Agricultural Economics & Development, 38*(4), 431-442. https://doi.org/10.22067/jead.2024.90678.1311

Abstract

The broiler chicken industry is a vital agricultural subsector in Kurdistan Province, Iran, with 716 production units in the province and a 5% growth from 2019 to 2024. However, there is no study to evaluate the comparative advantage indices or competitive capacity of broiler chicken production in Kurdistan Province. This study aims to assess these factors using the Policy Analysis Matrix (PAM) for 2023. Findings indicate that Kurdistan Province has a comparative advantage in broiler chicken production, as shown by the Domestic Resource Cost (DRC) ratio and Social Benefit-Cost Ratio (SBCR), across all production capacities. The Nominal Protection Coefficient (NPC) for the product reveals that the market price of live broiler chicken is lower than its shadow price, effectively imposing indirect taxation on producers. Conversely, the NPC for inputs shows that input shadow prices exceed market prices, suggesting indirect subsidies for poultry inputs. The Effective Protection Coefficient (EPC), which combines these effects, indicates effective government support for the industry. Competitiveness indices suggest that broiler chicken production in Kurdistan Province is viable both domestically and internationally. The findings suggest that the broiler chicken industry of Kurdistan could compete in regional markets, particularly Iraq market, even without supportive policies in form of input subsidies, provided price suppression is eliminated and market-based pricing is implemented. Thereby, this study suggested transitioning from interventionist policies to establishing a transparent and competitive market infrastructure to ensure sustainable growth in broiler chicken production.

Keywords: Broiler chicken, Comparative advantage, Export competitiveness, Policy Analysis Matrix

https://doi.org/10.22067/jead.2024.90678.1311

Introduction

Agriculture, as the primary sector responsible for food security and raw inputs to the industrial sector, holds a significant position in development process. Development process is discussed in framework of transformation structure referring to diminishing share of agriculture in employment and income in favor of industrial and service sectors. In livelihood farming, agricultural sector often accounts for a larger share of employment and gross domestic product (GDP).

Although theoretical economic perspectives generally discourage public sector intervention in the economy, the significant role of agriculture in production and employment within developing economies has consistently led governments in these regions to prioritize support for agricultural activities. In contrast, developed economies, in alignment with the World Trade Organization's (WTO) Agreement on Agriculture (AOA), have transitioned toward low-intervention strategies to enhance the competitiveness of agricultural products. This shift has influenced resource allocation and technological advancements in agricultural production, shaping production methods and capital-labor ratios (Bowers, 1995).

According to official statistics from Central Bank of Iran, the contribution of agricultural sector to GDP was 10.42 percent in 2022, based on constant prices from 2016 (Central Bank of Iran, 2023). In Iran, the subsectors within agriculture can facilitate entry into international markets and reduce the economy's dependency on oil exports. Among these, the poultry industry is a significant subsector, as it meets a substantial portion of the country's protein requirements (Shahbazi & Javanbakht, 2019).

Chicken meat is particularly appealing due to its increasing demand, shorter production cycles, and quicker financial turnover (Moreki, 2011; Ezeh *et al.*, 2012). The production of chicken meat plays a vital role in agricultural development in several ways. Firstly, its short production cycle and rapid financial returns make it a stable and quick source of income for producers. Secondly, technical advantages, such as favorable feed conversion ratios and independence from climatic conditions, enable continuous and stable production. Thirdly, the speed of production and return on investment in the poultry sector position it as a driving force for agricultural development, contributing to economic growth through job creation, protein supply, and foreign exchange earnings. Hence, the direct relationship between chicken meat production and agricultural development is undeniable (Benalywa *et al.*, 2019).

Per capita chicken meat consumption in Iran is higher than developing countries and the global average due to factors such as the high cost of substitute goods like red meat. According to the World Population Review (2024) statistics, per capita chicken meat consumption in Iran was 24.31 kg in 2022, which is higher than the global average of 16.9 kg, and also the average of chicken consumption in developing countries, around 15 kg. This has driven the growth and expansion of the poultry industry, establishing chicken meat as a strategic product in the national economy (Moslehi, 2020).

The chicken meat industry in Iran is heavily reliant on imported feed inputs. Thus, fluctuations in exchange rates, global prices, or restrictions on imports significantly increase production costs. This price hike, caused by market imbalances, reduces the welfare of producers and consumers and poses a severe threat to national food security (Mirzaei *et al.*, 2023). The Iranian government, aiming to enhance the competitiveness and production of chicken meat, has implemented policies such as subsidies for imported poultry feed and guaranteed purchase of chicken meat to regulate the market, resulting in increased production. Studies by the Poultry Support Center of the Livestock Affairs Support Company indicate that feed cost is responsible to approximately 70% of the cost production of chicken meat (Mashaiekhi & Hajizadeh Fallah, 2011). As most of these inputs are imported, government interventions and a multi-tier exchange rate system created asymmetry in the transparency of the product’s real prices, complicating the evaluation of its technical and economic efficiency. Therefore, the Policy

Analysis Matrix (PAM) serves as a suitable tool for analyzing the overall impact of government policies and assessing the relative advantages of production. PAM is a highly effective tool for assessing the comparative advantages, competitiveness, and policy impact analysis (Saptana *et al.,* 2022). The Policy Analysis Matrix is a dual-accounting technique that succinctly summarizes the budgetary information of on-farm and off-farm activities (Rahmani & Layani, 2023). By employing this matrix, the market profitability and social profitability of producing a specific product can be measured. The difference between these two profitability levels reveals the impact of various policies on the production process. This framework is built on a straightforward profit relationship. This matrix also demonstrates the outcomes of implemented policies, aiding in optimizing production patterns to reduce product costs.

Benalywa *et al.* (2019) used PAM to evaluate the relative advantage of broiler production in Malaysia and concluded the significant influence of feed input prices. Pilusa *et al.* (2020) examined South Africa's poultry industry and revealed the government's supportive policies towards producers and a comparative advantage in chicken meat production in 2017. Onyoni and Basil (2022) assessed the relative competitiveness of livestock trade under the African Continental Free Trade Area (AfCFTA) framework. Hasanvand *et al.* (2010) analyzed the comparative advantage of nomadic livestock farming in Lorestan Province. Their findings supported the establishment of cattle farming units in Khorramabad. Mohammadi *et al.* (2019) examined the relative advantages of grain production in Pishva County, concluding that greenhouse products, such as cucumbers and bell peppers, hold regional and national export potential.

According to the Kurdistan Agriculture Organization, the agricultural output of Kurdistan Province increased by 600,000 tons in 2023. The number of broiler farms rose to 716 units, contributing significantly to meeting the province's protein requirements. Notably, Iran ranked 13th globally in chicken meat production in 2022, producing 2.1 million tons (FAO, 2024). Given Iran's strategic geographic position for exporting agricultural and livestock products, the necessity of planning and adopting appropriate policies to manage resource allocation and production based on comparative advantage becomes increasingly evident (Youzi *et al.*, 2022). Moreover, Kurdistan Province produced 81,000 tons of chicken meat in 2022, ranking 10th among Iran's provinces in chicken meat production. Additionally, it holds the top position among western provinces, highlighting its potential for exporting chicken meat to Iraq due to shared borders.

Given the significance of the topic, numerous studies have focused on determining comparative advantages. The concept of comparative advantage was first introduced by Bruno (1972), evaluating the textile industry in Palestine. Various studies have also explored the relative advantages of livestock products domestically and internationally. For instance, Beres and Mészáros (2011) analyzed the impact of the Common Agricultural Policy (CAP) on livestock production in four Central European countries (V4). Their findings indicated that the Czech Republic improved its comparative advantage in cattle production, and Slovakia did so in poultry production. However, Poland and Slovakia experienced a decline in lamb production.

The review of previous studies revealed research focusing on determining the existence of comparative advantages in favorable regions. Despite Kurdistan's significant potential in chicken meat production and its notable contribution to national output, no comprehensive study with these objectives has been conducted in this province. The goal of this study is evaluation of the (i) comparative advantage of broiler chicken production in Kurdistan; and (ii) domestic and export competitiveness of Kurdistan's poultry sector.

Materials and Methods

Policy Analysis Matrix

The inputs utilized in the poultry industry

were divided into two categories: (i) tradable inputs, which include livestock production inputs such as soybean meal, corn, barley, various vaccines, feed additives, day-old chicks, disinfectants, electricity, gas, and tradable machinery; and (ii) domestic inputs, which encompass capital, water, labor, and certain non-tradable machinery. Table 1 is structured the PAM format.

Table 1- A general format of Policy analysis matrix

	Revenues	Costs		Profit
		Tradeable inputs	Domestic inputs	
Private (Market) Prices	A	B	C	D
Social (Shadow) Prices	E	F	G	H
Divergences	I	J	K	L

Source: Elsedig *et al.* (2015)

Private profits, D, equal A minus B minus C. Social profits, H, equal E minus F minus G. Output transfers, I, equal A minus E. Input transfers, J, equal B minus F. Factor transfers, K, equal C minus G. Net transfers, L, equal D minus H (also equal I minus J minus K). Using the Policy Analysis Matrix, three groups of indicators can be calculated, including following indicators (Haji Rahimi, 2015, Elsedig *et al.*, 2015):

- Comparative Advantage Indicators: These include Domestic Resource Cost (DRC) and Social Cost-Benefit Ratio (SCB).
- Support Indicators: These include the Nominal Protection Coefficient (NPC), Nominal Protection Coefficient on Inputs (NPCI), and Effective Protection Coefficient (EPC).
- Competitiveness Indicators: These include domestic competitiveness (CDC) and export competitiveness indices (CEC).

$$DRC = \frac{G}{E-F} \quad (1)$$

$$SCB = \frac{G+E}{E} \quad (2)$$

$$NPC = \frac{A}{E} \quad (3)$$

$$NPCI = \frac{B}{F} \quad (4)$$

$$EPC = \frac{A-B}{E-F} \quad (5)$$

$$CDC = \frac{B+C}{A} \quad (6)$$

$$CEC = \frac{B+C}{E} \quad (7)$$

The Domestic Resource Cost (DRC) reflects the ratio of the shadow price of domestic inputs to the difference between shadow revenues and shadow costs of tradable inputs. If $0 < DRC < 1$, it indicates the existence of a relative advantage; otherwise, if the index is greater than one or less than zero, it signals the absence of a relative advantage.

The Social Cost-Benefit Ratio (SCB) is a simpler index that is always positive. If the SCB is less than one, it indicates a relative advantage in producing the target product.

For the Nominal Protection Coefficient (NPC), a value greater than one indicates support for producers, such as indirect subsidies provided by the government. Conversely, a value less than one signifies indirect tax burdens on producers.

The Nominal Protection Coefficient for Input (NPCI) reflects the taxation or subsidization of inputs. A value greater than one indicates taxation on poultry inputs, while a value less than one reflects subsidies provided for such inputs.

The Effective Protection Coefficient (EPC) combines the NPC and NPCI to represent the net impact of government policies on inputs and producer income. If the EPC is greater than one, it signifies effective governmental support for producers; if less than one, it indicates a lack of support (Elsedig *et al.*, 2015).

The Domestic Competitiveness Coefficient (CDC) measures domestic cost

competitiveness. A value greater than one indicates that the product lacks domestic cost competitiveness. Similarly, the Export Competitiveness Coefficient (CEC) evaluates export cost competitiveness, where a value greater than one indicates that the product lacks export cost competitiveness (Elsedig *et al.*, 2015)

Shadow Prices Calculation

Shadow prices reflect the economic value of resources in a free and competitive market without external interventions. Given the challenges of ensuring competitive conditions in broiler chicken production, global prices are used as substitutes for shadow prices of output and inputs. Shadow revenue was calculated by the border price of broiler chicken as a net importing product in Iran, i.e. CIF (Cost, Insurance, and Freight). For tradable inputs, most poultry inputs are imported; hence, their shadow prices are the CIF prices plus the cost of domestic transportation (Rahmani & Layani, 2023; Rezaee *et al.*, 2010).

For non-tradable domestic inputs, such as buildings, labor, and water, shadow prices are calculated differently, often using the opportunity cost of the inputs. In this study, the approach proposed by Karaman *et al.* (2023) for Turkey served as the basis for shadow cost calculations due to its comprehensiveness and credibility.

The shadow exchange rate required for calculating the shadow price of the product and tradable inputs was derived using the absolute purchasing power parity (PPP) theory. Specifically, the shadow exchange rate was calculated by equation 8, as below (Beckmann & Czudaj, 2013):

$$E = \frac{P_g}{P_{dg}} \quad (8)$$

In which, P_g represents the price of one ounce of gold in Rials, and P_{dg} represents the price of one ounce of gold in dollars.

Data and Sampling

The statistical population of the study consists of 716 broiler poultry farms in Kurdistan Province, Iran. The sampling method used is stratified random sampling, with the classification criterion being the capacity of the broiler chicken farms. In this method, an equal number of samples are randomly selected from each stratum based on the classification criterion. Accordingly, a total of 132 broiler poultry farms in Kurdistan Province were examined in 2023. The required data were collected through the completion of questionnaires from poultry farms in selected counties of Kurdistan Province, as well as through interviews with experts from the Kurdistan Provincial Agriculture Organization and the Livestock Support Services Center.

Results and Discussion

The required inputs to produce one kilogram of live broiler chicken meat in Kurdistan province for the studied farms in 2023, summarized in Table 2. As observed, producing each kilogram of live broiler chicken in the studied farms requires, on average, 1.9 kilograms of feed, 0.2 liters of fossil fuel, 2 kilowatt-hours of electricity, and 6 liters of water. These metrics highlight the resource-intensive nature of broiler production while providing a quantitative basis for evaluating its environmental and economic implications.

Table 2- Required inputs to produce one kilogram of live chicken meat

Feed (kg)	Fuel (liter)	Electricity (kWh)	Water (liter)
1.9	0.2	2	6

Source: research findings

Table 3 shows the distribution of poultry farms by capacity. The Table reveals a distinctive pattern in the distribution of capacities among the broiler farms in the province. Most farms fall into two capacity categories: 11,500–20,000 birds (43.9%) and 11,000 birds or fewer (21.1%), collectively accounting for approximately 65% of all farms. Farms with capacities of 20,500–30,000 birds (25.1%) hold the next rank. Larger farms, with

capacities of 30,500–40,000 birds, comprise only 5.7%, while extra-large farms with capacities exceeding 40,500 birds include 4.2% of farms. The average capacity is 20,486 birds, with a standard deviation of 10,289, indicating considerable variation in the size and capacity of farms, ranging from small family-run operations to large industrial complexes.

Table 3- Frequency distribution of broiler farms in Kurdistan province based on capacity, 2023

Classification of chicken farms based on capacity	Frequency	Valid Percent	Cumulative Percent
11000 pieces and less	151	21.1	21.1
11500-20000 pieces	314	43.9	64.9
20500-30000 pieces	180	25.1	90.1
30500-40000 pieces	41	5.7	95.8
40500 pieces and more	30	4.2	-
Sum	716	100	100

Source: research findings

Table 4 presents detailed data on the production output and nominal income of broiler farmers, categorized by flock size. The income is derived from two primary sources: the sale of live chickens and the sale of manure. These revenue streams are integral to the calculation of the Profitability and Margin Analysis (PAM) for broiler farming operations. The Table illustrates how farm capacity influences production and revenue. For instance, a farm with a capacity of 20,000 birds yields an average of 52,640 kilograms of live chicken per production cycle. At an average market price of 58,500 Tomans (10 Rials) per kilogram, this production generates a gross income of 3,079,440,000 Tomans (10 Rials). Additionally, the sale of manure provides supplementary income, further enhancing the farm's overall revenue. These figures highlight the economic dynamics of broiler farming across different flock sizes, offering valuable insights for assessing profitability, resource allocation, and scalability in this agricultural sector.

Table 4- Production values of representative broiler farms in different capacities of Kurdistan province, 2023

Capacity	Product type	Price type	Production (kg)	Price (10 Rials)	Revenue (10 Rials)
10 thousand pieces	Chicken meat	Market	26320	58500	1539720000
		Shadow	26320	69000	1816080000
	Animal manure	Market	16000	1400	22400000
		Shadow	16000	3200	51200000
20 thousand pieces	Chicken meat	Market	52640	58500	3079440000
		Shadow	52640	69000	3632160000
	Animal manure	Market	30000	1400	42000000
		Shadow	30000	3200	96000000
30 thousand pieces	Chicken meat	Market	78960	58500	4619160000
		Shadow	78960	69000	5448240000
	Animal manure	Market	45000	1400	63000000
		Shadow	45000	3200	144000000
40 thousand pieces	Chicken meat	Market	105280	58500	6158880000
		Shadow	105280	69000	7264320000
	Animal manure	Market	52000	1400	72800000
		Shadow	52000	3200	166400000

Source: Research findings

The results of comparative advantage indices presented in Table 5 indicate that the Domestic Resource Cost (DRC) ratio is less than one, signifying a comparative advantage in chicken production in Kurdistan Province. In other words, the actual cost of producing this

product locally is lower than its import cost, demonstrating the province's competitive advantage. These results (Table 5) align with those of Rahmani & Layani (2023), Beres & Mészáros (2011), and Benalywa *et al.* (2019).

For a broiler farm with 10,000 birds, the DRC ratio is 0.683, indicating that for every unit of value-added in foreign exchange (e.g., $1 or equivalent), only 0.63 units of domestic resources are consumed. This indicates that domestic production is economically efficient because the domestic cost of producing the good is less than its potential value in international markets.

Similarly, the Social Benefit-Cost (SCB) ratio for a 10,000-bird farm is calculated at 0.922. This indicates that for every unit of social benefit (e.g., $1 or equivalent) generated, the associated social costs amount to 0.922 units. Consequently, the production of broiler chickens in Kurdistan Province results in a net social profit. This demonstrates that the production activity generates more social benefits than it incurs in social costs, highlighting its social efficiency and overall positive contribution to society.

When considering both the DRC and SCB ratios, the most efficient scale of broiler farming in Kurdistan Province is found to be farms with a capacity of 20,000 birds. These farms achieve a DRC value of 0.579 and an SCB ratio of 0.881, indicating strong economic and social efficiency. The lower DRC suggests a comparative advantage in production, while the SCB value underscores the significant net social benefits provided by this scale of operation.

Table 5- Comparative advantage indices in different capacities in broiler farms in Kurdistan province, 2023

	10 thousand pieces	20 thousand pieces	30 thousand pieces	40 thousand pieces
Domestic Resource Cost (DRC)	0.683	0.579	0.692	0.837
Social Cost Benefit (SCB)	0.922	0.881	0.963	0.983

Source: research findings

Coefficient of Export Competitiveness (CEC) and Coefficient of Domestic Competitiveness (CDC), are reported in Table 6.

The Coefficient of Export Competitiveness (CEC) is an economic indicator that measures the competitiveness of a product or industry in international markets. It evaluates the relationship between domestic production costs and international market prices. The ECI values for farms with 10,000, 20,000, 30,000, and 40,000 birds are 0.714, 0.634, 0.715, and 0.778, respectively, indicating that the domestic cost of broiler chicken meat producing in Kurdistan Province is lower than its international market price.

On the other hand, the Coefficient of Domestic Competitiveness (CDC) is an economic indicator that measures how efficiently a product can compete with imports in the domestic market. It compares the domestic cost of production to the price of imported alternatives.

According CEC and CDC ratios, the most efficient scale of broiler farming in Kurdistan Province is also found to be farms with a capacity of 20,000 birds.

Table 6- Indices of competitiveness in different capacities in broiler farms in Kurdistan province, 2033

	10 thousand pieces	20 thousand pieces	30 thousand pieces	40 thousand pieces
Coefficient of Export Competitiveness (CEC)	0.714	0.634	0.715	0.778
Coefficient of Domestic Competitiveness (CDC)	0.853	0.755	0.867	0.877

Source: research findings

Table 7 provides a comprehensive overview of the policy impact indices. The Nominal Protection Coefficient (NPC), which measures the ratio of domestic market prices to shadow (social) prices for outputs, reveals that broiler chicken farms in Kurdistan Province operating with flock sizes of 10,000, 20,000, 30,000, and 40,000 birds have NPC values of 0.824, 0.836,

0.832, and 0.851, respectively. These values, all below one, indicate that the domestic market prices for chicken are lower than their corresponding shadow prices. This disparity suggests the existence of implicit taxation on producers, as they are unable to capture the full social value of their output in the market.

In contrast, the NPC values for production inputs highlight a different dynamic. The domestic costs of inputs are lower than their global counterparts, primarily due to government interventions such as foreign exchange subsidies allocated to imported feed ingredients. These policies have effectively reduced the financial burden on producers, thereby enhancing their cost competitiveness.

The Effective Protection Coefficient (EPC), which integrates the effects of both output and input price distortions, further elucidates the overall impact of government policies. For farms with 10,000, 20,000, 30,000, and 40,000 birds, the EPC values were calculated as 1.267, 1.369, 1.266, and 1.518, respectively. Since all these values exceeded one, it can be concluded that the combined effect of input subsidies and implicit taxation on outputs results in a net positive support for the poultry sector. The EPC values not only underscore the significant role of government policies in shaping the economic landscape of poultry production but also highlight the potential for targeted policy adjustments to further optimize resource allocation and enhance producer welfare.

Table 7- Policy impact indices in different capacities in broiler farms in Kurdistan province, 20323

	10 thousand pieces	20 thousand pieces	30 thousand pieces	40 thousand pieces
Nominal Protection Coefficient for Output (NPC)	0.824	0.836	0.832	0.851
Nominal Protection Coefficient for Input (NPIC)	0.778	0.875	0.779	0.776
Effective Protection Coefficient (EPC)	1.267	1.369	1.266	1.518

Source: research findings

Conclusion

This study aimed to estimate and analyze the comparative advantages, policy impact indices, and competitive capacity of broiler chicken production in Kurdistan Province, Iran. To achieve this, the Policy Analysis Matrix (PAM) was employed to evaluate the state of broiler farming across the province. The findings from the indices of Domestic Resource Cost (DRC) and Social Benefit-Cost (SBC) Ratio, as well as the indices of internal and export competitiveness, including the Coefficient of Export Competitiveness (CEC) and the Coefficient of Domestic Competitiveness (CDC), indicated that broiler chicken production in Kurdistan Province possesses both comparative and competitive advantages.

The results of the policy impact analysis and support indices revealed that although the government has implemented a form of price suppression policy by controlling product prices in the domestic market, it has effectively supported domestic production through policies favoring imported inputs. Specifically, government interventions such as the allocation of subsidized exchange rates for the importation of key inputs, primarily soybean and corn, have led to positive values for the Nominal Protection Coefficient for inputs (NPCI). Consequently, the overall impact of government policies, as reflected in the Effective Protection Coefficient (EPC), shows that the subsidies for inputs outweigh the implicit taxation on product prices through price suppression. In summary, the government has provided real and effective support for broiler chicken production in Kurdistan Province.

Based on this study results, it can be concluded that the broiler chicken industry in Kurdistan Province enjoys significant comparative and competitive advantages. While government interventions have contributed to the expansion of production, they have also led to inefficiencies in the market by

increasing the intensity of resource use, particularly water, fuel, and electricity. These inefficiencies have constrained the sector's ability to adapt to market dynamics and achieve environmental sustainability.

Thus, it can be argued that policy reforms aimed at improving transparency and efficiency in the broiler chicken market in Kurdistan Province and across Iran would be beneficial. Specifically, adopting a more flexible price management system, gradually reducing subsidies, and promoting technological advancements could foster a more sustainable and competitive broiler chicken industry. Such reforms would enable the sector to meet domestic demand and expand into export markets. Through these measures, the broiler chicken industry in Kurdistan could play a more significant role in regional economic growth, food security, and rural development.

Acknowledgement

The authors would like to express their profound gratitude to the University of Kurdistan for providing essential resources, guidance, and academic support that greatly facilitated the successful completion of this research. Additionally, we extend our sincere appreciation to the Kurdistan Agriculture Organization for their invaluable assistance, particularly in offering access to critical data, expert consultations, and logistical support throughout the study. Their collaborative efforts and commitment to advancing agricultural research have been instrumental in achieving the objectives of this work. We are deeply thankful for their encouragement and contributions, which have significantly enriched the quality and impact of this research.

References

1. Beckmann, J., & Czudaj, R.L. (2013). Oil prices and effective dollar exchange rates. *International Review of Economics & Finance*, *27*(C), 621-636. https://doi.org/10.1016/j.iref.2012.12.002
2. Benalywa, Z.A., Ismail, M.M., Shamsudin, M.N., & Yusop, Z. (2019). Assessing the comparative advantage of broiler production in Peninsular Malaysia using policy analysis matrix. *Tropical animal health and production*, *51*, 321-327. https://doi.org/10.1007/s11250-018-1690-8
3. Beres, D., & Mészáros, K. (2011). Competitiveness and comparative advantages in agriculture (livestock approach). *Problems of World Agriculture (Problemy Rolnictwa Światowego)*, *11*(26), 1-9. https://ideas.repec.org/a/ags/polpwa/195333.html
4. Bowers, J. (1995). Sustainability, agriculture, and agricultural policy. *Environment and Planning A*, *27*(8), 1231-1243.
5. Bruno, M. (1972). Domestic resource costs and effective protection: Clarification and synthesis. *Journal of Political Economy*, *80*(1), 16-33. https://www.jstor.org/stable/1830128
6. Central Bank of the Islamic Republic of Iran (CBI). (2023). Annual Review for 1401 (2022/23). https://cbi.ir/simplelist/AnnualReview_en.aspx
7. Ezeh, C.I., Anyiro, C.O., & Chukwu, J.A. (2012). Technical efficiency in poultry broiler production in Umuahia Capital Territory of Abia State, Nigeria. *Greener Journal of Agricultural Sciences*, *2*(1), 001-007. https://gjournals.org/GJAS/archive/vol-2-1-jan-2012/ezeh-et-al.html
8. Elsedig, E.A.A., Mohd, M.I., & Fatimah, M.A. (2015). Assessing the competitiveness and comparative advantage of broiler production in Johor using policy analysis matrix. *International Food Research Journal*, *22*, 1-20. https://www.cabidigitallibrary.org/doi/pdf/10.5555/20153093595
9. Food and Agriculture Organization (FAO). (2024). FAOSTAT, Crops and livestock products. https://www.fao.org/faostat/en/#data/QCL
10. Haji-Rahim, M. (2015). A social profit analysis of self-sufficiency policy for wheat production in Iran. *International Journal of Scientific Management and Development*, *3*(1), 807-810.

https://ideas.repec.org/a/ags/ijamad/246098.html
11. Hasanvand, M., Karbasi, A., & Darijani, A. (2010). An Analysis of the Relative Advantage of Livestock Nomads in Lorestan Province, A Case Study of Khorramabad, Eighth Biennial Agriculture Economics Conference of Iran, P:889-900. (In Persian). https://doi.org/10.22059/jrur.2021.308771.1546
12. Iran Feed Industry Association. (IRFIA). (2022). Iran Animal Feed Market, 3rd Edition. https://irfia.ir/shfolder/pdf/FM2022.pdf
13. Karaman, S., Taşcıoğlu, Y., & Bulut, O.D. (2023). Profitability and cost analysis for contract broiler production in Turkey. *Animals*, *13*(13), 2072. https://doi.org/10.3390/ani13132072
14. Mashaiekhi, S., & Hajizadeh Fallah, M. (2011). The study on the effective factors in Chicken meat market in Iran: An application of Vector Autoregression model. *Economic Research Journal 11*(40), 131-154. (In Persian). https://joer.atu.ac.ir/article_2567_en.html
15. Mirzaei, A., Azarm, H., Valizadeh, N., Sobhani, S.M.J., & Ziaee, A. (2023). The effects of price explosion and compensatory policies on food security: The Case of chicken meat consumers in Iran. *Iran Agricultural Research*, *42*(2), 49-58. (In Persian). https://doi.org/10.22099/iar.2024.48881. 1565
16. Mohammadi, Y., Shalalvand, M., & Rezapour, K. (2018). Determining an optimal agronomic cropping pattern in productive units by analyzing the regional and national comparative advantages. *Iranian Journal of Agricultural Economics and Development Research*, *49-2*(4), 719-734. (In Persian). https://dor.isc.ac/dor/20.1001.1.20084838.1397.49.4.12.8
17. Moreki, J.C. (2011). Challenges in small-scale broiler production in Botswana. *Journal of Agricultural Technology, 7*(6), 1579-1587.
18. Moslehi, H. (2020). *The collection of world experience publications in the field of agriculture and natural resources; Comparing the status of broiler production in Iran with other countries* (No. 19), 1 Edition. Publication of Agricultural Education. Tehran. Iran. (In Persian)
19. Nikzad, M., Hosseini, S.S., Salami, H., Chizari, A., & Ahady, A. (2022). Evaluation and analysis of comparative advantages, competitiveness and the effects of supportive policies on selected products of Afghanistan's economic-agricultural zones. *Iranian Journal of Agricultural Economics and Development Research, 53*(2), 301-323. (In Persian). https://doi.org/10.22059/ijaedr. 2021.315282.668985
20. Onyoni, R., & Basil, D. (2022). *Enhancing the Competitiveness of Kenya's Livestock Products in the African Continental Free Trade Area: Revealed Comparative Advantage.* Kenya Institute for Public Policy Research and Analysis. ZDB-ID 2982267-1. - Vol. no. 290.
21. Pilusa, K. V., Belete, A., & Baloi, V.A. (2020). Analyzing chicken meat production comparative advantage of South Africa. *African Journal of Agricultural Research*, *16*(6), 843-849. https://doi.org/10.5897/AJAR2019.14604
22. Rahmani, R., & Layani, Gh. (2023). Investigating the economic effects of government policies on broiler production units in Fars province. *Journal of Agricultural Economic Research*, *15*(3), 28-43. (In Persian). https://doi.org/10.30495/jae.2023.30100.2328
23. Rezaee, A., Chizari, A., & Nakhaei, N. (2010). Investigation of protective policies & comparative advantage of production & export of onion: (Case study: Esfahan). *Journal of Agricultural Economics and Development*, *24*, 1-20. https://doi.org/10.22067/jead2.v1389i2.3929
24. Saptana, S., Sayekti, AL., Perwita, AD., Sayaka, B., Gunawan, E., & Sukmaya, SG. (2022) Analysis of competitive and comparative advantages of potato production in Indonesia. *PLOS One*, *17*(2), e0263633. https://doi.org/10.1371/journal.pone
25. Shahbazi, A., & Javanbakht, O. (2019). Studying the production structure of poultry units in Masjed Soleyman town. *Journal of Animal Science Research*, *29*(2), 15-29. (In Persian). https://animalscience.tabrizu.ac.ir/article_9485.html
26. Youzi, F., Ghaderzadeh, H., & Farzinpour, A. (2022). Economic analysis of production period

of broiler breeding in Kurdistan province: A case of Sanandaj, Kamyaran and Divandareh cities. *Iranian Journal of Animal Science Research*, *14*(2), 255-266. (In Persian). https://dor.isc.ac/dor/20.1001.1.20083106.1401.14.2.9.2

27. World Population Review (2024). Chicken Consumption by Country. Available at: https://worldpopulationreview.com/country-rankings/chicken-consumption-by-country

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مقاله پژوهشی

جلد ۳۸، شماره ۴، زمستان، ۱۴۰۳، ص. ۴۳۱-۴۴۲

تحلیل رقابت‌پذیری و تأثیر سیاست‌ها بر تولید مرغ گوشتی در استان کردستان: رویکرد ماتریس تحلیل سیاستی

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تاریخ دریافت: ۱۴۰۳/۰۸/۱۸

تاریخ پذیرش: ۱۴۰۳/۱۰/۰۸

چکیده

صنعت پرورش مرغ گوشتی از مهمترین زیر بخش‌های کشاورزی در ایران و استان کردستان است. در استان کردستان، تعداد واحدهای پرورش مرغ گوشتی فعال ۷۱۶ واحد می‌باشد و در سال‌های اخیر (از سال ۱۳۹۸ تا حالا) تعداد این واحدها ۵ درصد رشد داشته است. با وجود اهمیت بالای این صنعت، تا زمان تدوین این مقاله، حتی یک پژوهش علمی در مورد محاسبه شاخص‌های مزیت نسبی و توان رقابتی تولید مرغ گوشتی در استان کردستان انجام نشده است. هدف پژوهش حاضر برآورد و بررسی شاخص‌های مزیت نسبی، شاخص‌های حمایت دولت و توان رقابت داخلی و صادراتی تولید گوشت مرغ در استان کردستان در سال ۱۴۰۲ با استفاده از الگوی ماتریس تحلیل سیاستی می‌باشد. نتایج حاصل از برآورد شاخص‌های مزیت نسبی شامل نسبت هزینه منابع داخلی و نسبت منفعت به هزینه اجتماعی حاکی از وجود مزیت نسبی برای تولید این محصول در استان کردستان در همه ظرفیت‌های تولید می‌باشد. نتایج حاصل از شاخص حمایت اسمی از محصول نشان داد که قیمت بازاری گوشت مرغ زنده در کشور پایین‌تر از قیمت سایه‌ای آن است و به عبارت دیگر از تولید کننده مالیات غیرمستقیم قیمتی اخذ شده است. نتایج محاسبه شاخص حمایت اسمی از نهاده نیز بیانگر آن است که قیمت سایه‌ای نهاده‌ها بیشتر از قیمت بازاری آن‌ها بوده است و یارانه غیرمستقیم به نهاده‌های مرغداری‌ها پرداخت شده است. نتایج برآورد شاخص حمایت مؤثر که برآیند حمایت اسمی محصول و حمایت اسمی نهاده‌ها را نشان می‌دهد، حاکی است که دولت در مجموع از تولید مرغ گوشتی در استان کردستان حمایت مؤثر کرده است. شاخص‌های توان رقابتی نیز برای محصول یاد شده بیانگر توانایی رقابت این محصول چه در سطح داخلی و چه در سطح بین‌الملل می‌باشد. به عبارت دیگر، حتی چنانچه دولت حمایت یارانه‌ای از نهاده‌ها را حذف کند، به شرطی که همزمان سرکوب قیمت محصول را نیز بردارد و تعیین قیمت را به بازار واگذار کند، تولید مرغ گوشتی در استان کردستان توان رقابتی لازم برای حضور در باز جهانی و بویژه بازار کشور دارای مرز مشترک با استان کردستان یعنی عراق را دارد. بر اساس این یافته‌ها، پیشنهاد می‌گردد به جای سیاست‌های مداخله گرانه در بازار محصول و نهاده‌های تولید مرغ گوشتی، به فراهم آوردن زیرساخت‌های بازار شفاف و رقابتی در تولید این محصول اولویت داده شود.

واژه‌های کلیدی: رقابت‌پذیری صادرات، ماتریس تحلیل سیاستی، مرغ گوشتی، مزیت نسبی کردستان

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https://doi.org/10.22067/jead.2024.90678.1311

Journal of Agricultural Economics & Development

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

Research Article
Vol. 38, No. 4, Winter 2025, p. 443-460

Group Decision-Making of Agricultural Stakeholders towards Sustainable Groundwater Resources Management: A Case Study in North Khorasan

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Received: 07-12-2024
Revised: 12-01-2025
Accepted: 18-01-2025
Available Online: 18-01-2025

How to cite this article:
Bahrami Nasab, M., Firoozzare, A., Dourandish, A., Sabouhi, M., & Ghorbani, M. (2025). Group decision-making of agricultural stakeholders towards sustainable groundwater resources management: A case study in North Khorasan. *Journal of Agricultural Economics & Development, 38*(4), 443-460. https://doi.org/10.22067/jead.2025.91123.1320

Abstract

Groundwater is a vital resource for agriculture in arid regions which its over-extraction has led to significant challenges of declining water levels and increased scarcity. This study addresses the urgent need for sustainable groundwater management by employing an inclusive group decision-making approach involving diverse stakeholders, with a focus on farmers. Overlooking the participation of farmers in the decision-making approach led to ineffective policies. Utilizing Multi-Criteria Decision-Making (MCDM) methods, specifically the fuzzy Shannon entropy and Fuzzy TOPSIS techniques, the research prioritizes strategies for reducing groundwater consumption in the Safi-Abad region of North Khorasan, Iran. Qualitative data from stakeholder interviews provided insights into the challenges and opportunities related to groundwater use, revealing two primary strategies: (i) transitioning to low water-demand crops; and (ii) adopting modern irrigation systems. These approaches not only promise significant reductions in water usage but also support sustainable agricultural practices. The findings highlighted the importance of stakeholder collaboration in implementing effective water management policies, ensuring responsible resource use, and securing long-term viability. This study served as a model for future research, advocating for mixed methods integrating qualitative and quantitative analyses to inform policy recommendations and improve water resource management.

Keywords: Agricultural water management, Decision-making, Farmers role, Stakeholder participation, Water conservation strategies

https://doi.org/10.22067/jead.2025.91123.1320

Introduction

Groundwater is a critical resource for agricultural production, particularly in arid and semi-arid regions where surface water is limited (Noori *et al*., 2021; Priyan, 2021). However, excessive and imbalanced groundwater extraction has led to declining groundwater levels, the drying up of wells, and exacerbated water scarcity, particularly in the agricultural sector (Noori *et al*., 2021).

Iran, located in an arid and semi-arid region, faces significant challenges in water resource management. Over the past decades, the per capita renewable water availability has drastically declined due to population growth, climate change, and inefficient agricultural practices (Madani, 2014; Ashraf *et al*., 2017). Recent studies indicate that Iran's renewable water resources have decreased from approximately 4,500 cubic meters per capita in the 1970s to less than 1,600 cubic meters per capita in recent years, pushing the country into a state of water stress (Emerald Expert Briefings, 2023). This alarming trend has resulted in severe water scarcity, particularly in agricultural regions where groundwater over-extraction has become a critical issue (Noori *et al*., 2021; Haghshenas Haghighi *et al*., 2024). A notable example of this crisis in Iran is the Safi-Abad plain in North Khorasan province, a dry region characterized by an arid climate, limited surface water resources, and heavy reliance on groundwater for agriculture. The salinization of the groundwater in this region is predominantly intensified by over-extraction, making forms of saline and brackish issues and the drying up of wells. Given that agriculture is the primary occupation in Safi-Abad and groundwater is the main water source, it is imperative to develop strategies to reduce groundwater extraction and ensure sustainable water management. Addressing these challenges requires a holistic approach to decision-making that considers the economic, environmental, and social impacts of water resource management (Meran *et al*., 2021; Moltz *et al*., 2020).

In real-world agricultural water resource decision-making, multiple stakeholders-including farmers, local authorities, water managers, and policymakers-play crucial roles. Each stakeholder brings unique knowledge, skills, and experiences that must be integrated into the decision-making process (Permono & Kurniati, 2024; Lee *et al*., 2022; Ahmadi *et al*., 2020). Given the complexity of factors influencing water consumption in agriculture, a single decision-maker cannot adequately address all aspects of the issue (Lee *et al*., 2022; Nouri *et al*., 2023). Therefore, group decision-making involving diverse stakeholders is essential to achieve precise and reliable outcomes (Khanzadi *et al*., 2009; Cai *et al*., 2004).

Recognizing the importance of stakeholder participation, this study examines group decision-making processes among agricultural stakeholders in the Safi-Abad region of North Khorasan province, Iran. By integrating the perspectives of farmers, policymakers, and water managers, this research aims to identify effective strategies for sustainable groundwater management and contribute to the broader discourse on water resource conservation in arid regions.

The scarcity and inappropriate use of water resources, particularly within the agricultural sector, have prompted research to increasingly focus on policies and strategies aimed at reducing water consumption. Multi-Criteria Decision-Making (MCDM) methods have gained considerable importance in recent years and are widely applied across various real-world contexts (Kacprzak, 2019). In agriculture, where multiple influential factors - such as farmer income, production costs, and water consumption levels - influence the selection of effective strategies for reducing water usage, a multi-criteria group decision-making approach is essential for identifying optimal solutions. This section provides a review of the literature on the application of MCDM in groundwater management (Table 1).

Table 1- Related literature on the application of MCDM in groundwater management

Authors	The study region	Methodology	Purpose of the study
Pocco *et al.* (2023)	Arid Zone Basin of the Atacama Desert (In South America), Caplina basin.	Analytical Hierarchy Process (AHP) - based GIS approach	Determining potential sources of groundwater using a Multi-Criteria Decision-Making technique with remote sensors
Tork *et al.* (2021)	Nekouabad area located in the central plateau of Iran	AHP and COPRAS	Determining the effectiveness and rank the scenarios for the modernization of surface water distribution system in reducing water withdrawal from the aquifers
Radmehr *et al.* (2022)	Iran	Combining hierarchical analysis and the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).	Proposes a new framework of strategic planning with multi-criteria decision-making to develop sustainable water management alternatives for large scale water resources systems
Hamidifar *et al.* (2023)	Iran	Analytical hierarchy process (AHP), Fuzzy-AHP, and technique for order preference by similarity to ideal solution (TOPSIS)	Examining the effective criteria for water supply projects in rural areas
Xuân Thảo & Nhung (2019)	Vietnam	Fuzzy MCDM models	Selection of the best water reuse application of the existing options
Ali & Khan (2020)	Pakistan	Fuzzy VIKOR method	Evaluating the impact of climate change on the agriculture sector
Alamanos *et al.* (2018)	Greek, lake Karla watershed	Multi attribute utility theory (MAUT), analytic hierarchy process (AHP), elimination and choice expressing reality (ELECTRE), and technique for order of preference by similarity to ideal solution (TOPSIS)	Evaluating water resource management (WRM) strategies and selecting the most appropriate among them
Garai & Garg (2022)	Purulia district, West Bengal, India	Multi-criteria decision making method for water resource management problems based on possibility measures under generalized single valued non-linear bipolar neutrosophic environment	Defining the available water resources in the agriculture field
Hadelan *et al.* (2020)	Croatia	Analytical hierarchy process (AHP),	Comparing and ranking three possible locations for the construction of an irrigation system in different parts of Croatia
Noori *et al.* (2021)	Gamasiab Basin in Kermanshah province, Iran	Fuzzy ELECTRE III	The main goal of the modified method is to better manage uncertainties in the evaluation process by considering both quantitative and qualitative criteria through group decision-making
Sheikhipoor *et al.* (2018)	Shahrekord aquifer, Iran	Simple additive weighting (SAW) and MTAHP, a hybrid of modified TOPSIS and analytic hierarchy process models.	Prioritizing groundwater management scenarios from an aquifer.
Pourmand *et al.* (2020)	Varamin region, Iran	Interval type-2 fuzzy sets combined with the TOPSIS model	optimizing the allocation of water and reclaimed wastewater across domestic, agricultural, and industrial sectors, and to restore groundwater quantity and quality
Yilmaz *et al.* (2010)	Gediz River Basin in Turkey	Simple additive weighting (SAW), compromise programming (CP) and technique for order preference by similarity to ideal solution (TOPSIS)	developing a water resource management model that facilitates indicator-based decisions, with respect to environmental, social and economic dimensions in a multiple criteria perspective

In most reviewed studies, the role of farmers as primary stakeholders in agricultural water

consumption decisions has been overlooked, leading to potential resistance during the implementation of top-down policies. This gap highlights the need for research that actively involves diverse stakeholders, particularly farmers, in decision-making processes aimed at reducing water consumption. Multi-Criteria Decision-Making (MCDM) methods, especially when integrated with fuzzy models, have proven effective in optimizing water allocation, reducing costs, and promoting sustainable water management practices. To bridge these gaps, this study utilizes F-Shannon's entropy and F-TOPSIS methods to support stakeholder-inclusive, region-specific decision-making for sustainable groundwater management in a drought-affected agricultural region of Iran. The paper is structured as follows: first, the case study and methodology are introduced; second, the results of applying F-Shannon's entropy and F-TOPSIS are presented; and finally, the findings and their implications are discussed.

Materials and Methods

The Study Region

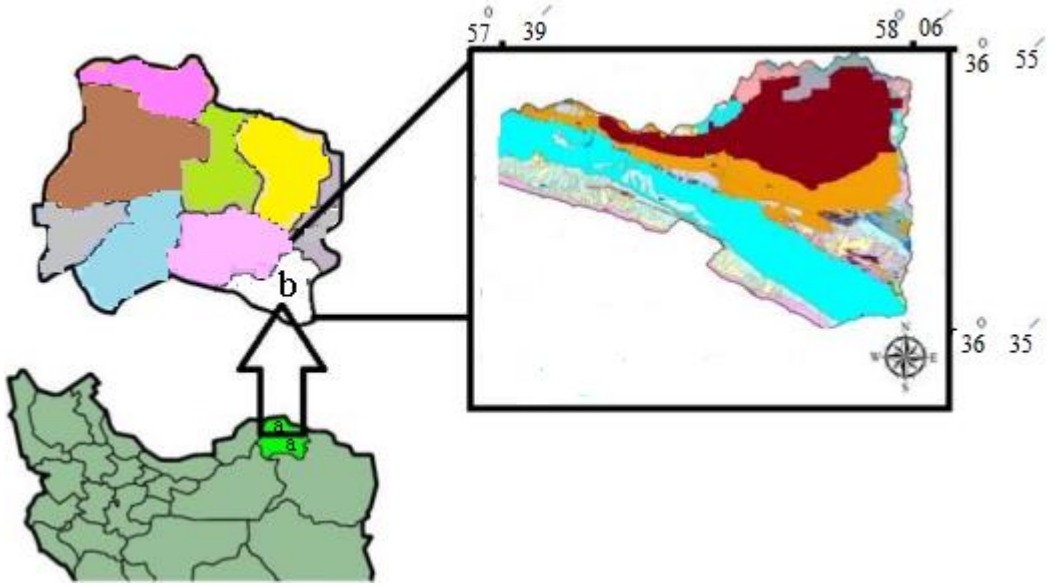

Figure 1- The geographical location of the study area in North Khorasan province, Iran
North Khorasan province, Iran
Safi-Abad rural district in North Khorasan province

The Safi-Abad plain, located in North Khorasan province, Iran, is a critical arid region characterized by limited precipitation, lack of permanent rivers, and scarce high-quality surface water resources. (Fig. 1). Groundwater accounts for approximately 79% of the total water consumption, with 90% used by the agricultural sector (Esfarayen Water Landscape, 2021). Given that farmers are the primary consumers of groundwater, their active participation in decision-making is essential for developing effective and acceptable water conservation strategies. This study employs the F-Shannon's entropy–F-TOPSIS hybrid approach to engage farmers as key stakeholders, ensuring sustainable groundwater use and enhancing the implementation of conservation measures in the region.

F-Shannon's Entropy –F- TOPSIS Hybrid Approach

The decision-making process involves identifying options and establishing criteria for selecting optimal strategies. Multi-Criteria Decision-Making (MCDM) techniques are used to rank these options, especially when multiple decision-makers (DMs) are involved to account for diverse priorities and subjective judgments (Kacprzak, 2020; Sadi-Nezhad & Damghani, 2010).

Fuzzy set theory, introduced by Zadeh (1965), provides a framework for handling ambiguity in evaluations. (Chen, 2000; Hatami-Marbini & Kangi, 2017). Fuzzy Group Decision-Making (FGDM) methods are effective in water resource management, particularly when decision-makers face constraints such as limited time or incomplete data (Kaya & Kahraman, 2010).

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), introduced by Hwang & Yoon (1981), evaluates alternatives based on their distances from the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS). Traditional TOPSIS relies on precise data, which is often unrealistic. To address this, fuzzy adaptations of TOPSIS have been developed, enabling decision-makers to handle ambiguity effectively (Chen, 2000; Hatami-Marbini & Kangi, 2017).

In MCDM, assigning weights to criteria is critical for aligning decisions with objectives. The fuzzy Shannon entropy method is particularly useful for determining weights when criteria are represented as fuzzy numbers, capturing uncertainty effectively (Mohammadi *et al.*, 2020). In this study, we combined the fuzzy Shannon entropy method with Fuzzy TOPSIS to support group decision-making among agricultural stakeholders, aiming to reduce groundwater consumption.

The extended Fuzzy TOPSIS for GDM

In this study, we employed an extended TOPSIS method based on fuzzy numbers to address group decision-making challenges. Unlike traditional approaches that aggregate individual decision matrices into a collective matrix using arithmetic or geometric means, our method utilizes all individual decision data without aggregation. This allows for a more nuanced ranking of alternatives and the identification of the optimal choice (Kacprzak, 2017). A key step in this method involves transforming the decision matrices provided by decision-makers (DMs) into matrices of alternatives. Each alternative's matrix is formed from assessments across all criteria as evaluated by all DMs (Kacprzak, 2020). The positive ideal solution (PIS) and negative ideal solution (NIS) are defined as matrices of maximum and minimum assessments, respectively. The distances of alternatives from the PIS and NIS are calculated as distances between matrices, and the coefficient of relative closeness to the PIS is used to rank alternatives and select the best option (Kacprzak, 2020).

In this section, the applied approach is presented. Consider an MCDM problem for group decision-making. Let $(m \geq 2)$ $\{A_1, A_2, \ldots, A_m\}$ be a discrete set of m feasible alternatives, $\{C_1, C_2, \ldots, C_n\}$ $(n \geq 2)$ be a finite set of criteria. $w = (w_1, w_2, \ldots, w_n)$ be the vector of criteria weights, such that $0 \leq w_j \leq 1$

Let $\{DM_1, DM_2, \ldots, DM_k\}$ $(k \geq 2)$ be a group of decision-makers.

Each DM presents a decision matrix in the following form:

$$X^K = \begin{array}{c} \\ A_1 \\ A_2 \\ \mathrm{M} \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \mathrm{L} & C_n \end{array} \\ \begin{bmatrix} x_{11}^k & x_{12}^k & \mathrm{L} & x_{1n}^k \\ x_{21}^k & x_{22}^k & \mathrm{L} & x_{2n}^k \\ \mathrm{M} & \mathrm{M} & \mathrm{M} & \mathrm{M} \\ x_{m1}^k & x_{m2}^k & \mathrm{L} & x_{mn}^k \end{bmatrix} \end{array} \quad (1)$$

where $x_{ij}^k = (a_{x_{ij}^k}, b_{x_{ij}^k}, c_{x_{ij}^k}, d_{x_{ij}^k})$ is a positive trapezoidal fuzzy number representing the rating of alternative $A_i\ (i = 1, 2, .., m)$ with respect to criterion $C_j = (j = 1, 2, .., n)$ provided by decision-maker $DM_k\ (k = 1, 2, .., K)$

A very popular way of constructing the fuzzy decision matrix X^K is to use linguistic variables to evaluate the ratings of alternatives concerning various criteria (Kacprzak, 2017; Hatami-Marbini & Kangi, 2017). Decision-makers (DMs) rate alternatives using linguistic expressions, which are then represented as trapezoidal fuzzy numbers to capture fuzzy judgments. Fig. 2 and Table 2 shows the fuzzy numbers represent the linguistic variables. These variables are used to characterize the performance rating of each alternative for each attribute (Hatami-Marbini & Kangi, 2017).

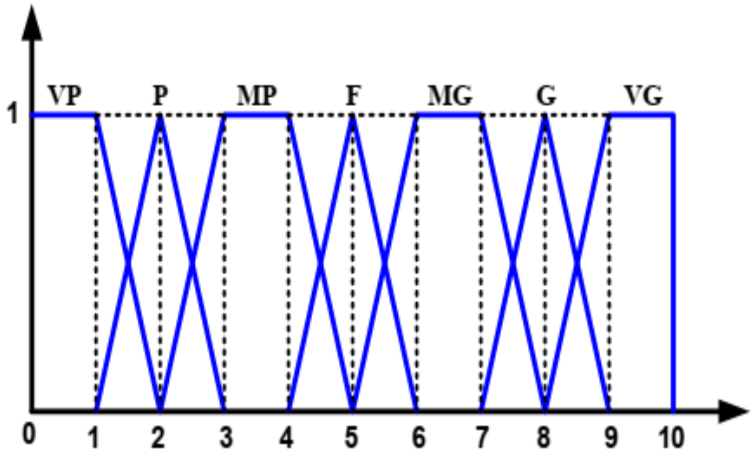

Figure 2- Performance rating of Alternatives

Table 2- The linguistic variables for the ratings of the alternatives and their representation by FNs

Linguistic variable	Fuzzy number
Very poor (VP)	(0, 0, 1, 2)
Poor (P)	(1, 2, 2, 3)
Medium poor (MP)	(2, 3, 4, 5)
Fair (F)	(4, 5, 5, 6)
Medium good (MG)	(5, 6, 7, 8)
Good (G)	(7, 8, 8, 9)
Very good (VG)	(8, 9, 10, 10)

Next, in order to ensure comparability of criteria, the fuzzy decision matrix X^{K} is normalized. The normalized fuzzy decision matrix

$$Y^{K} = \begin{array}{c} \\ A_1 \\ A_2 \\ \text{M} \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \text{L} & C_n \end{array} \\ \begin{bmatrix} y_{11}^{k} & y_{12}^{k} & \text{L} & y_{1n}^{k} \\ y_{21}^{k} & y_{22}^{k} & \text{L} & y_{2n}^{k} \\ \text{M} & \text{M} & \text{M} & \text{M} \\ y_{m1}^{k} & y_{m2}^{k} & \text{L} & y_{mn}^{k} \end{bmatrix} \end{array} \qquad (2)$$

is calculated using the following formulas:

$$y_{ij}^{k} = \begin{cases} \left(\dfrac{a_{x_{ij}^{k}}}{max_i d_{x_{ij}^{k}}}, \dfrac{b_{x_{ij}^{k}}}{max_i d_{x_{ij}^{k}}}, \dfrac{c_{x_{ij}^{k}}}{max_i d_{x_{ij}^{k}}}, \dfrac{d_{x_{ij}^{k}}}{max_i d_{x_{ij}^{k}}} \right) \\ \left(\dfrac{min_i a_{x_{ij}^{k}}}{d_{x_{ii}^{k}}}, \dfrac{min_i a_{x_{ij}^{k}}}{c_{x_{ii}^{k}}}, \dfrac{min_i a_{x_{ij}^{k}}}{b_{x_{ii}^{k}}}, \dfrac{min_i a_{x_{ij}^{k}}}{a_{x_{ii}^{k}}} \right) \end{cases} \qquad (3)$$

Using the vector of criteria weights $w = (w_1, w_2, ..., w_n)$, the weighted normalized fuzzy decision matrix is calculated for each DM.

$$V^{K} = \begin{array}{c} \\ A_1 \\ A_2 \\ \text{M} \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \text{L} & C_n \end{array} \\ \begin{bmatrix} V_{11}^{k} & V_{12}^{k} & \text{L} & V_{1n}^{k} \\ V_{21}^{k} & V_{22}^{k} & \text{L} & V_{2n}^{k} \\ \text{M} & \text{M} & \text{M} & \text{M} \\ V_{m1}^{k} & V_{m2}^{k} & \text{L} & V_{mn}^{k} \end{bmatrix} \end{array} \qquad (4)$$

Where

$$v_{ij}^{k} = w_j y_{ij}^{k} = (w_j a_{y_{ij}^{k}}, w_j b_{y_{ij}^{k}}, w_j c_{y_{ij}^{k}}, w_j d_{y_{ij}^{k}}) \qquad (5)$$

The matrices V^k form the basis for the construction of weighted normalized fuzzy decision matrices for each alternative A_i.

$$W^{i} = \begin{array}{c} \\ DM_1 \\ DM_2 \\ \mathrm{M} \\ DM_k \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \mathrm{L} & C_n \end{array} \\ \begin{bmatrix} v_{i1}^{1} & v_{i2}^{1} & \mathrm{L} & v_{in}^{1} \\ v_{i1}^{2} & v_{i1}^{2} & \mathrm{L} & v_{in}^{2} \\ \mathrm{M} & \mathrm{M} & \mathrm{M} & \mathrm{M} \\ v_{i1}^{k} & v_{i2}^{k} & \mathrm{L} & v_{in}^{k} \end{bmatrix} \end{array} \quad (6)$$

Matrices W^i constitute the basis for the ranking of the alternatives and the selection of the best one using the fuzzy TOPSIS method.

The positive ideal solution A^+ is determined as follows:

$$A^{+} = \begin{array}{c} \\ DM_1 \\ DM_2 \\ \mathrm{M} \\ DM_k \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \mathrm{L} & C_n \end{array} \\ \begin{bmatrix} v_1^{1+} & v_2^{1+} & \mathrm{L} & v_k^{1+} \\ v_1^{2+} & v_2^{2+} & \mathrm{L} & v_n^{2+} \\ \mathrm{M} & \mathrm{M} & \mathrm{M} & \mathrm{M} \\ v_1^{k+} & v_2^{k+} & \mathrm{L} & v_n^{k+} \end{bmatrix} \end{array} \quad (7)$$

Where $v_j^{k+} = \max_i v_{ij}^{k}$ and the negative ideal solution A^- is determined as follows:

$$A^{-} = \begin{array}{c} \\ DM_1 \\ DM_2 \\ \mathrm{M} \\ DM_k \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \mathrm{L} & C_n \end{array} \\ \begin{bmatrix} v_1^{1-} & v_2^{1-} & \mathrm{L} & v_k^{1-} \\ v_1^{2-} & v_2^{2-} & \mathrm{L} & v_n^{2-} \\ \mathrm{M} & \mathrm{M} & \mathrm{M} & \mathrm{M} \\ v_1^{k-} & v_2^{k-} & \mathrm{L} & v_n^{k-} \end{bmatrix} \end{array} \quad (8)$$

Where $v_j^{k-} = \min_i v_{ij}^{k}$

Next, the distances of each alternative A_i represented by matrix W^i from PIS are calculated as follows:

$$d_i^{+} = \sum_{k=1}^{K} \sum_{j=1}^{n} d\left(v_{ij}^{k}, v_j^{k+}\right) \quad (9)$$

And from NIS

$$d_i^{-} = \sum_{k=1}^{K} \sum_{j=1}^{n} d\left(v_{ij}^{k}, v_j^{k-}\right) \quad (10)$$

Using these distances, the relative closeness coefficient RC_i to PIS for each alternative A_i is calculated as follows:

$$RC_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}} \quad (11)$$

According to the descending values of RC_i all alternatives A_i are rank ordered and the best one is selected.

Fuzzy Shannon's Entropy Method

In multi-criteria decision-making (MCDM), decision-makers must assign weights to criteria to reflect their relative importance. While these weights may lack direct economic significance, they are essential for modeling decision-making preferences and structures (Izadikhah & Salehi, 2014; Opricovic & Tzeng, 2004).

The evaluation of criteria often leads to diverse opinions highlighting the need for a systematic approach to weight assignment. Weighting methods can be categorized into two types: subjective and Objective methods. Objective methods are particularly useful when reliable subjective weights are difficult to obtain. In this study, we employ the Shannon entropy method, extended for imprecise data by Hosseinzadeh Lotfi and Fallahnejad (2010), to calculate criteria weights. This approach is effective for handling interval and fuzzy data, ensuring a robust and objective weighting system (Jafarnejad *et al.*, 2012).

The steps of fuzzy Shannon's entropy are explained as follows:

Step 1: Transforming Fuzzy Data into Interval Data Using α-Level Sets

The α-level set of a fuzzy variable $\tilde{x}_{ij}$ is defined as the set of elements that belong to the fuzzy variable $\tilde{x}_{ij}$ with a membership of at least α i.e,

$$\left(\tilde{x}_{ij}\right)_{\alpha} = \left\{\tilde{x}_{ij} \in R \mid \mu_{\tilde{x}_{ij}}(\tilde{x}_{ij}) \geq \alpha\right\} \quad (12)$$

The α-level set can also be expressed in the following interval form:

$$[x_{ij}{}^{l}, x_{ij}{}^{U}] = \left[\left(\tilde{x}_{ij}\right)_{\alpha}{}^{L}, \left(\tilde{x}_{ij}\right)_{\alpha}{}^{U}\right] = \quad (13)$$

$$\left[min_{\tilde{x}_{ij}}\left\{x_{ij} \in R \mid \mu_{x_{ij}}(x_{ij}) \geq \alpha\right\}, max_{\tilde{x}_{ij}}\left\{x_{ij} \in R \mid \mu_{x_{ij}}(x_{ij}) \geq \alpha\right\}\right]$$

Where $0 < \alpha \leq 1$. By setting different levels of confidence, namely 1-α, fuzzy data are transformed into different α-level sets $\{(\tilde{x}_{ij})_{\alpha} \mid 0 < \alpha \leq 1\}$, which are all intervals (Jafarnejad *et al*., 2012).

Step 2: The Normalized Decision Matrix

Suppose A_1, A_2,…, A_m are m possible alternatives among which decision-makers have to choose, C_1 , C_2 ,…, C_n are criteria with which alternative performance is measured. X_{ij} is the rating of alternative A_i with respect to criterion C_j, which is not known exactly; we only know that $X_{ij} \in [X_{ij}^L , X_{ij}^U]$. An MCDM problem with interval data can be expressed in matrix format as follows (Izadikhah & Salehi, 2014):

	C_1	C_2	....	C_n
A_1	$[X_{11}^L, X_{11}^U]$	$[X_{12}^L, X_{12}^U]$		$[X_{1n}^L, X_{1n}^U]$
A_2	$[X_{21}^L, X_{21}^U]$	$[X_{32}^L, X_{22}^U]$		$[X_{2n}^L, X_{2n}^U]$
.				
.				
A_m	$[X_{m1}^L, X_{m1}^U]$	$[X_{m2}^L, X_{m2}^U]$		$[X_{mn}^L, X_{mn}^U]$

(14)

Now we calculate the normalized decision matrix as follows. The normalized values $\bar{n}_{ij}{}^L$ and $\bar{n}_{ij}{}^U$ are calculated as:

$$\bar{n}_{ij}{}^L = \frac{x_{ij}{}^L}{\sum_{j=1}^{m}\left[x_{ij}{}^L + x_{ij}{}^U\right]} \quad j = 1, \ldots, m \ , \ i = 1, \ldots, n \tag{15}$$

$$\bar{n}_{ij}{}^U = \frac{x_{ij}{}^U}{\sum_{j=1}^{m}\left[x_{ij}{}^L + x_{ij}{}^U\right]} \quad j = 1, \ldots, m \ , \ i = 1, \ldots, n \tag{16}$$

This normalization is the norm L1 version of the normalization method proposed by Jahanshahloo *et al*. (2006). The interval $[\bar{n}_{ij}{}^L , \bar{n}_{ij}{}^U]$ is the normalized of interval $[X_{ij}{}^L , X_{ij}{}^U]$. The normalization method mentioned above preserves the property that the ranges of normalized interval numbers belong to [0, 1].

Step 3: Calculation of the Concentration Index for Each Criterion with Interval Data

This is accomplished by solving the following two non-linear models:

$$E_j^L = min(-\frac{1}{\ln(m)})\sum_{i=1}^{m} x_{ij}{}^U \ln(x_{ij}{}^U) \tag{17}$$

Subject to

$$\bar{n}_{ij}{}^L \leq x_{ij} \leq \bar{n}_{ij}{}^U$$

$$E_j^U = max(-\frac{1}{\ln(m)})\sum_{i=1}^{m} x_{ij}{}^L \ln(x_{ij}{}^L) \tag{18}$$

Subject to

$$\bar{n}_{ij}{}^L \leq x_{ij} \leq \bar{n}_{ij}{}^U$$

After some simple calculation, we have:

$$E_j^L = (-\frac{1}{\ln(m)})\sum_{i=1}^{m} n_{ij}{}^U \ln(n_{ij}{}^U) \tag{19}$$

$$E_j^U = (-\frac{1}{\ln(m)})\sum_{i=1}^{m} n_{ij}{}^L \ln(n_{ij}{}^L) \tag{20}$$

Therefore, we have $E_j^L \leq E_j^U$

Step 4: The Amount of Dispersal for Each

Criterion

$$d_j^L = 1 - E_j^U \quad (21)$$

$$d_j^U = 1 - E_j^L \quad (22)$$

Therefore, we have $d_j^L \leq d_j^U$

Step 5: Calculation of the Weights of Criteria

$$W_j{}^L = \frac{d_j^L}{\sum_{j=1}^{n}\left[d_j^L + d_j^U\right]} \quad (23)$$

$$W_j{}^U = \frac{d_j^U}{\sum_{j=1}^{n}\left[d_j^L + d_j^U\right]} \quad (24)$$

Therefore, we $w_j{}^L \leq w_j{}^U$ and the interval weight of criterion Cj is $[w_j{}^L , w_j{}^U]$.

Selection of Participants

In Multi-Criteria Decision Making (MCDM), there are no rigid rules for determining the selection of experts. However, in previous studies, experts are generally chosen based on two key criteria: i. Subject-specific knowledge and industry experience, and ii. The author's professional and personal connections, often utilizing convenience sampling.

In this study, in-person interviews were conducted with various stakeholder groups from relevant organizations, including: Managers of the North Khorasan Agriculture Organization, Staff from the North Khorasan Regional Water Company, and Managers from the North Khorasan Department of Environment and Exemplary farmers. The questionnaire, consisting primarily of open-ended items, was designed to explore their views and experiences regarding reducing groundwater consumption in agriculture. A total of 57 interviews were conducted (see Table 3).

Table 3- Frequency of Stakeholder Participation

Participants Class	Number of Participants
Managers and staff members of the Regional Water Company	2
Agriculture Organization Managers	3
Managers of Natural Resources and Environment Organization	2
Farmers	50
Total	57

Results

According to previous studies review, upstream documents, expert opinions, and insights from university professors, as well as the environmental conditions of the region, the most significant strategies and criteria were identified (see Table 4).

Table 4- Strategies and criterions

Criteria	C_1	" Increasing income from cultivation"	Alternatives (Strategies)	$A_{1,}$	Reducing a portion of the cultivated area in exchange for receiving cash subsidies.
	C_2	"Reducing production costs"		$A_{2,}$	Reducing groundwater extraction in exchange for cash subsidies.
	C_3	"Preventing the depletion of groundwater reserves"		$A_{3,}$	Increasing Water Prices in Exchange for Higher Crop Prices
	C_4	" Job creation in the agricultural sector"		$A_{4,}$	Adopting Modern Irrigation Systems in Place of Traditional ones.
	C_5	"Increasing retention in rural areas"		$A_{5,}$	Prioritizing the cultivation of autumn crops to utilize rainfall in fall, winter, and spring.
	C_6	" Increasing crop yields "		$A_{6,}$	Reducing the cultivated area of high water-demanding crops and replacing them with low water-demanding crops.
	C_7	" Preventing Drought Occurrence"			
	C_8	"Groundwater quality (preventing water salinity)"			
	C_9	"Preventing land subsidence"			
	C_{10}	" Enhancing soil quality"			
	C_{11}	"Reducing energy consumption in water extraction"			
	C_{12}	"Preserving The Natural Ecosystem (Flora and Fauna)"			

Table 5- The weight of criteria calculated using method fuzzy Shannon entropy method

No.			$[E_j^L, E_j^U]$	$[D_j^L, D_j^U]$	$[W_j^L, W_j^U]$	W_j
1	C_1	" Increasing income from cultivation"	[0.434357, 0.866069]	[0.133931,0.565643]	[0.016167, 0.06828]	0.042224
2	C_2	"Reducing production costs"	[0.528068, 0.812953]	[0.187047, 0.471932]	[0.022579,0.056968]	0.039774
3	C_3	" Preventing the depletion of groundwater reserves "	[0.508902, 0.813787]	[0.186213, 0.491098]	[0.022478, 0.059282]	0.04088
4	C_4	" Job creation in the agricultural sector"	[0.43132, 0.870612]	[0.129388, 0.56868]	[0.015619, 0.068647]	0.042133
5	C_5	"Increasing retention in rural areas"	[0.479694, 0.840219]	[0.159781, 0.520306]	[0.019288, 0.062808]	0.041048
6	C_6	" Increasing crop yields "	[0.418325, 0.873132]	[0.126868, 0.581675]	[0.015315, 0.070216]	0.042765
7	C_7	" Preventing Drought Occurrence"	[0.402583, 0.866895]	[0.133105, 0.597417]	[0.016068 ,0.072116]	0.044092
8	C_8	"Groundwater quality (preventing water salinity)"	[0.502786, 0.820005]	[0.179995, 0.497214]	[0.021728, 0.06002]	0.040874
9	C_9	"Preventing land subsidence"	[0.486124, 0.830636]	[0.169364, 0.513876]	[0.020444, 0.062031]	0.041238
10	C_{10}	" Enhancing soil quality"	[0.450453, 0.847213]	[0.1527877, 0.54954]	[0.018443, 0.066337]	0.04239
11	C_{11}	" Reducing energy consumption in water extraction "	[0.50606, 0.823436]	[0.176564, 0.49394]	[0.021313, 0.059625]	0.040469
12	C_{12}	"Preserving The Natural Ecosystem (Flora and Fauna)"	[0.431427, 0.870811]	[0.129189, 0.568573]	[0.015595, 0.068634]	0.042114

Table 6- The results of TOPSIS fuzzy method regarding the prioritization of strategies to reduce the consumption of underground water.

No.			d_i^-	d_i^+	RC_i	Rank
1	$A_{1,}$	Reducing a portion of the cultivated area in exchange for receiving cash subsidies.	10.66619	8.367691	0.560379	4
2	$A_{2,}$	Reducing groundwater extraction in exchange for cash subsidies.	11.12382	7.87999	0.585347	3
3	$A_{3,}$	Increasing Water Prices in Exchange for Higher Crop Prices	3.65702	15.28742	0.193039	6
4	$A_{4,}$	Adopting Modern Irrigation Systems in Place of Traditional ones.	13.40303	5.577716	0.706138	2
5	$A_{5,}$	Prioritizing the cultivation of autumn crops to utilize rainfall in fall, winter, and spring.	7.158848	11.84819	0.376642	5
6	$A_{6,}$	Reducing the cultivated area of high water-demanding crops and replacing them with low water-demanding crops.	14.29616	4.700346	0.752568	1

The strategies for reducing groundwater consumption were prioritized using the Multi-Criteria Decision-Making (MCDM) model. This approach was chosen due to its ability to handle complex decision-making processes involving multiple criteria and stakeholder preferences. First, the relative importance of the criteria was determined using the fuzzy Shannon entropy method**.** This method was particularly useful for addressing uncertainties in stakeholder inputs and ensuring a robust weighting process. By incorporating fuzzy logic, the model effectively captures the vagueness and subjectivity inherent in stakeholder judgments, leading to more reliable results. The results, summarized in Table 5 revealed that the criterion "Preventing Drought Occurrence" (C_7) had the highest weight, indicating its critical importance in the decision-making process. This finding underscores the stakeholders' concern about the long-term impacts of drought on agricultural sustainability.

Next, the strategies were evaluated and prioritized using the Fuzzy TOPSIS method. This method was selected for its ability to handle imprecise data and provide a clear ranking of alternatives based on their proximity to ideal solutions. The results, presented in Table 6, identified the following ranking of strategies:

1. Reducing the cultivated area of high water-demanding crops and replacing them with low water-demanding crops (Strategy 6).
2. Adopting modern irrigation systems in place of traditional ones (Strategy 4).
3. Reducing groundwater extraction in exchange for cash subsidies (Strategy 2).
4. Reducing a portion of the cultivated area in exchange for receiving cash subsidies (Strategy 5).
5. Prioritizing the cultivation of autumn crops to utilize rainfall in fall, winter, and spring (Strategy 3).
6. Increasing water prices in exchange for higher crop prices (Strategy 1).

This prioritization, based on factors such as water savings, economic impacts, and social acceptability, provides a clear roadmap for stakeholders to implement effective measures for sustainable groundwater management. The high ranking of crop replacement and modern irrigation systems reflects their potential to address both water scarcity and agricultural productivity challenges. These strategies are particularly relevant in regions where groundwater depletion has reached critical levels, threatening both food security and environmental stability.

Conclusion and Discussion

This study highlights the urgent need for innovative strategies to address groundwater depletion in agriculture. The over-extraction of groundwater, driven by population growth and climate change, poses a significant threat to food security and environmental sustainability. Without immediate action, the continued depletion of groundwater resources could lead to irreversible ecological damage and severe socio-economic consequences. The magnitude of the challenge is compounded by increasing frequency of droughts and the rising demand for water due to expanding urban populations and agricultural needs. By combining stakeholder insights with MCDM techniques, the research identified two key strategies: transitioning to low water-demand crops and adopting modern irrigation systems.

The top-ranked strategy, transitioning from high water-demanding crops to low water-demanding alternatives, aligns with global evidence supporting this approach. For instance, Boser *et al*. (2024) found that switching to lower water-intensity crops in California agriculture could reduce water consumption by up to 93%. Similarly, Davis *et al*. (2017) demonstrated that replacing existing crops with more suitable alternatives in specific areas of the U.S. could improve water resource efficiency. While the overall water use reduction from these crop replacements was modest (about 5%), significant local water savings were achieved, particularly in drought-prone regions like California. These findings highlight the potential of this strategy to

significantly reduce water use, especially in regions facing severe water scarcity. Moreover, recent studies show that adopting such crop strategies could potentially reduce farmers' vulnerability to water price fluctuations and ensure more stable agricultural productivity in the long term.

In addition to reducing water consumption, the adoption of low water-demand crops can contribute to rural development by diversifying income sources for farmers. In many regions, reliance on a single high water-demand crop has led to economic vulnerability due to price fluctuations and water scarcity. By introducing alternative crops, farmers can spread their risks and tap into emerging markets for niche products, such as organic or drought-resistant varieties. This diversification can strengthen local economies and improve livelihoods in rural communities.

The second-ranked strategy, adopting modern irrigation systems, has also proven effective in reducing water waste**.** Modern irrigation technologies, such as drip and sprinkler systems, enable precise water application, minimizing losses due to evaporation and runoff. These systems are particularly beneficial in arid and semi-arid regions, where water resources are limited and must be used efficiently**.** Studies such as Çebi *et al*. (2023) reported water savings of 66–73% when drip irrigation replaced traditional flood irrigation in rice farming. Similarly, Tsakmakis *et al.* (2017) and Leghari *et al*. (2024) demonstrated that modern irrigation systems not only conserve water but also improve crop yields. These results underscore the importance of investing in advanced irrigation technologies to optimize water use in agriculture. In addition to the water efficiency gains, studies have shown that modern irrigation practices can also lead to better uniformity in crop yields, further improving farm productivity.

Modern irrigation systems also offer opportunities for integrating renewable energy sources, further enhancing their sustainability. Solar-powered irrigation pumps, for example, can provide a clean and cost-effective alternative to conventional diesel-powered systems. This combination of water-saving technologies and renewable energy can reduce greenhouse gas emissions and promote climate-resilient agriculture. Moreover, the adoption of smart irrigation systems equipped with sensors and IoT technology allows for real-time monitoring and control, ensuring optimal water use based on crop needs and weather conditions. Such precision in water delivery helps farmers respond more effectively to fluctuating climate conditions, such as prolonged dry spells or unseasonal rainfall.

These strategies not only reduce water consumption but also enhance agricultural productivity and economic outcomes. To support their implementation, policymakers should provide financial incentives, technical training, and market access for low water-demand crops. For example, subsidies for seeds and equipment, as well as guaranteed purchase agreements for low water-demand crops, can encourage farmers to adopt these practices. Additionally, investments in modern irrigation infrastructure are essential to ensure sustainable water management in the region. Governments and agricultural organizations should collaborate to promote the widespread adoption of these technologies through subsidies, awareness campaigns, and capacity-building programs. Public-private partnerships can play a crucial role in scaling up these initiatives and ensuring their long-term success.

To facilitate the transition to sustainable agricultural practices, it is vital to address the knowledge gap among farmers regarding new technologies and crop management techniques. Training programs, extension services, and demonstration projects can help farmers understand the benefits and operational aspects of modern irrigation systems and low water-demand crops. Collaborations with agricultural research institutes and universities could also accelerate the development and dissemination of region-specific crop management strategies. Furthermore, fostering farmer-to-farmer learning networks can accelerate the diffusion of best practices and innovations within the agricultural community.

Future research should focus on evaluating

the long-term impacts of these strategies and exploring additional innovative practices to further enhance water sustainability in agriculture. For instance, integrating renewable energy sources into irrigation systems or developing drought-resistant crop varieties could offer additional benefits. Rainwater harvesting, on the other hand, can supplement groundwater supplies during dry periods, providing a buffer against water scarcity.

Another promising area for future research is the development of integrated water resource management (IWRM) frameworks that consider the interconnections between groundwater, surface water, and atmospheric water. Such frameworks can help optimize water allocation across different sectors, including agriculture, industry, and domestic use.

By embracing these enhancements, the agricultural sector can contribute significantly to sustainable water resource management, ensuring food security in an increasingly resource-constrained world. The findings of this study provide a foundation for policymakers, researchers, and practitioners to develop and implement effective solutions for groundwater conservation, ultimately contributing to the resilience and sustainability of agricultural systems globally. Ultimately, the success of these strategies depends on the collective efforts of all stakeholders, including governments, farmers, researchers, and private sector actors. Collaborative governance models that prioritize participatory decision-making and equitable benefit-sharing can foster trust and cooperation among stakeholders, paving the way for transformative change in water management practices.

References

1. Ahmadi, A., Kerachian, R., Skardi, M.J.E., & Abdolhay, A. (2020). A stakeholder-based decision support system to manage water resources. *Journal of Hydrology, 589,* Article 125138. https://doi.org/10.1016/j.jhydrol.2020.125138
2. Alamanos, A., Mylopoulos, N., Loukas, A., & Gaitanaros, D. (2018). An integrated multicriteria analysis tool for evaluating water resource management strategies. *Water, 10*(12), 1795. https://doi.org/10.3390/w10121795
3. Ali, I., & Khan, N. (2022). Evaluating the impact of climate change on the agriculture sector of Pakistan using multi-criteria decision making (MCDM). *Natural and Applied Sciences International Journal (NASIJ), 3*, 72-84. https://doi.org/10.47264/idea.nasij/3.2.6
4. Ashraf, S., AghaKouchak, A., Alizadeh, A., Mousavi Baygi, M., Moftakhari, H.R., Mirchi, A., Anjileli H., & Madani, K. (2017). Quantifying anthropogenic stress on groundwater resources. *Scientific Reports*, *7*(1), 1-12. https://doi.org/10.1038/s41598-017-12877-4.
5. Boser, A., Caylor, K., Larsen, A., Pascolini-Campbell, M., Reager, J., & Carleton, T. (2024). Field-scale crop water consumption estimates reveal potential water savings in California agriculture. *Nature Communications, 15,* 2366. https://doi.org/10.1038/s41467-024-46031-2.
6. Cai, X., Lasdon, L., & Michelsen, A. (2004). Group decision making in water resources planning using multiple objective analysis. *Journal of Water Resources Planning and Management, 130,* 4–14. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:1(4)
7. Çebi, U., Özer, S., Öztürk, O., Aydın, B., & Çakır, R. (2023). Yield and water productivity of rice grown under different irrigation methods. *The Journal of Agricultural Science*, *161*(3), 387–397. https://doi.org/10.1017/S0021859623000308.
8. Chen, C.T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems, 114*, 1-9. https://doi.org/10.1016/S0165-0114(97)00377-1.
9. Davis, K.F., Seveso, A., Rulli, M.C., & D'Odorico, P. (2017). Water savings of crop redistribution in the United States. *Water, 9*(2), 83. https://doi.org/10.3390/w9020083.
10. Garai, T., & Garg, H. (2022). Multi-criteria decision making of water resource management

problem (in agriculture field, Purulia district) based on possibility measures under generalized single valued non-linear bipolar neutrosophic environment. *Expert Systems with Applications, 205*, 117715. https://doi.org/10.1016/j.eswa.2022.117715.

11. Hadelan, L., Jež Rogelj, M., Gugić, J., Crnčan, A., & Zrakić Sušac, M. (2020). Multi- criteria evaluation of locations for irrigation system implementation. *Irrigation and Drainage, 69.* https://doi.org/10.1002/ird.2512.
12. Haghshenas Haghighi, M., & Motagh, M. (2024). Uncovering the impacts of depleting aquifers: A remote sensing analysis of land subsidence in Iran. *Science Advances, 10*(19), eadk3039. https://doi.org/10.1126/sciadv.adk3039.
13. Hamidifar, H., Ghorbani, M., Bakhshandeh, M., & Gholami, S. (2023). A multi-criteria multidimensional model for optimal selection of rural water supply systems. *Aqua, 72.* https://doi.org/10.2166/aqua.2023.028.
14. Hatami-Marbini, A., & Kangi, F. (2017). An extension of fuzzy TOPSIS for a group decision making with an application to Tehran Stock Exchange. *Applied Soft Computing, 52*, 1084-1097. https://doi.org/10.1016/j.asoc.2016.09.021
15. Hosseinzadeh Lotfi, F., & Fallahnejad, R. (2010). Imprecise Shannon's entropy and multi-attribute decision making. *Entropy, 12*, 53-62. https://doi.org/10.3390/e12010053
16. Hwang, C.-L., & Yoon, K.P. (1981). *Multiple attribute decision making: Methods and applications. A state-of-the-art survey.* Springer-Verlag. https://doi.org/10.1007/978-3-642-48318-9
17. Izadikhah, M., & Salehi, A. (2014). A novel method to extend SAW for decision-making problems with interval data. *Decision Science Letters, 3,* 225–236. https://doi.org/10.5267/j.dsl.2013.11.001.
18. Jafarnejad Chaghooshi, A., Fathi, M.R., & Kashef, M. (2012). Integration of fuzzy Shannon's entropy with fuzzy TOPSIS for industrial robotic system section. *Journal of Industrial Engineering and Management (JIEM), 5*(1), 102-114. https://doi.org/10.3926/jiem.397
19. Jahanshahloo, G.R., Lotfi, F.H., & Izadikhah, M. (2006). Extension of the TOPSIS method for decision-making problems with fuzzy data. *Applied Mathematics and Computation, 181*(2), 1544-1551. https://doi.org/10.1016/j.amc.2006.02.057
20. Kacprzak, D. (2017). Objective weights based on ordered fuzzy numbers for fuzzy multiple criteria decision-making methods. *Entropy, 19*(7), 373. https://doi.org/10.3390/e19070373.
21. Kacprzak, D. (2019). A doubly extended TOPSIS method for group decision making based on ordered fuzzy numbers. *Expert Systems with Applications, 116,* 243-254. https://doi.org/10.1016/j.eswa.2018.09.023.
22. Kacprzak, D. (2020). An extended TOPSIS method based on ordered fuzzy numbers for group decision making. *Artificial Intelligence Review, 53,* 2099–2129. https://doi.org/10.1007/s10462-019-09728-1
23. Kaya, T., & Kahraman, C. (2010). Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul. *Energy, 35*, 2517–2527. https://doi.org/10.1016/j.energy.2010.02.051.
24. Khanzadi, M., Nasirzadeh, F., Eftekhari, N., & Hassani, S. M. H. (2009, August 20-21). Selection of the optimal project execution system using fuzzy multi-criteria decision-making and group opinion aggregation. *In Proceedings of the Fifth International Project Management Conference*. Tehran, Iran.
25. Lee, S.-G., Adelodun, B., Ahmad, M.J., & Choi, K.S. (2022). Multi-level prioritization analysis of water governance components to improve agricultural water-saving policy: A case study from Korea. *Sustainability, 14*(6), 3248. https://doi.org/10.3390/su14063248
26. Leghari, S.J., Hu, K., Wei, Y., Wang, T., & Laghari, Y. (2024). Modelling the effects of cropping systems and irrigation methods on water consumption, nitrogen fates, and crop yields in the North

China Plain. *Computers and Electronics in Agriculture, 218*, 108677. https://doi.org/10.1016/j.compag.2024.108677
27. Madani, K. (2014). Water management in Iran: What is causing the looming crisis? *Journal of Environmental Studies and Sciences*, *4*(4), 315-328. https://doi.org/s13412-014-0182-z
28. Meran, G., Siehlow, M., & von Hirschhausen, C. (2021). Integrated water resource management: Principles and applications. In G. Meran, M. Siehlow, & C. von Hirschhausen (Eds.), The Economics of Water (pp. 23–121). Springer. https://doi.org/10.1007/978-3-030-48485-9_3.
29. Mohammadi, M., Zandhasami, H., & Yazdani, H. (2020). Identification and ranking of collaborative entrepreneurship mechanisms as a type of corporate entrepreneurship using hybrid method (fuzzy Shannon entropy and fuzzy ARAS). *Industrial Technology Development*, *18*(42), 31–52.
30. Moltz, H., Wallace, C., Sharifi, E., & Bencala, K. (2020). Integrating sustainable water resource management and land use decision-making. *Water, 12*, 2282. https://doi.org/10.3390/w12082282.
31. Noori, A., Bonakdari, H., Salimi, A.H., & Gharabaghi, B. (2021). A group multi-criteria decision-making method for water supply choice optimization. *Socio-Economic Planning Sciences,* 77, 101006. https://doi.org/10.1016/j.seps.2020.101006
32. Noori, R., Maghrebi, M., Mirchi, A., Tang, Q., Bhattarai, R., Sadegh, M., Noury, M., Torabi Haghighi, A., Kløve, B., & Madani, K. (2021). Anthropogenic depletion of Iran's aquifers. *Proceedings of the National Academy of Sciences of the United States of America, 118*(25), e2024221118. https://doi.org/10.1073/pnas.2024221118
33. Nouri, M., Homaee, M., Pereira, L.S., & Bybordi, M. (2023). Water management dilemma in the agricultural sector of Iran: A review focusing on water governance. *Agricultural Water Management, 288*, 108480. https://doi.org/10.1016/j.agwat.2023.108480.
34. Opricovic, S., & Tzeng, G.-H. (2004). Multi-criteria decision making methods: A comparative study. *European Journal of Operational Research, 156*(3), 445–455. https://doi.org/10.1016/j.ejor.2003.08.012.
35. Permono, B., & Kurniati, A. (2024). Decision-making processes in resource management: Lessons from the agriculture sector. *Journal of Resource Management and Decision Engineering*, *3*(2), 13-23. https://doi.org/10.61838/kman.jrmde.3.2.3.
36. Pocco, V., Chucuya, S., Huayna, G., Ingol-Blanco, E., & Pino-Vargas, E. (2023). A multi-criteria decision-making technique using remote sensors to evaluate the potential of groundwater in the arid zone basin of the Atacama Desert. *Water, 15*(7), 1344. https://doi.org/10.3390/w15071344
37. Pourmand, E., Mahjouri, N., Hosseini, M., & Nik-Hemmat, F. (2020). A multi-criteria group decision-making methodology using interval type-2 fuzzy sets: Application to water resources management. *Water Resources Management, 34*, 1-26. https://doi.org/10.1007/s11269-020-02657-7
38. Priyan, K. (2021). Issues and challenges of groundwater and surface water management in semi-arid regions. In Groundwater Resources Development and Planning in the Semi-Arid Region (pp. 1-17). https://doi.org/10.1007/978-3-030-68124-1_1
39. Radmehr, A., Bozorg-Haddad, O., & Loaiciga, H. (2022). Integrated strategic planning and multi-criteria decision-making framework with its application to agricultural water management. *Scientific Reports, 12*, 8406. https://doi.org/ 10.1038/s41598-022-12194-5.
40. Sadi-Nezhad, S., & Damghani, K. K. (2010). Application of a fuzzy TOPSIS method based on modified preference ratio and fuzzy distance measurement in assessment of traffic police centers performance. *Applied Soft Computing Journal, 10*, 1028-1039.
41. Sheikhipoor, B., Javadi, S., & Banihabib, M. E. (2018). A hybrid multiple criteria decision-making model for the sustainable management of aquifers. *Environmental Earth Sciences, 77*. https://doi.org/10.1007/s12665-018-7894-4.

42. Tork, H., Javadi, S., & Hashemy Shahdany, S.M. (2021). A new framework of a multi-criteria decision making for agriculture water distribution system. *Journal of Cleaner Production, 306*, 127178. https://doi.org/10.1016/j.jclepro.2021.127178
43. Tsakmakis, I., Kokkos, N., Pisinaras, V., Papaevangelou, V., Hatzigiannakis, E., Arampatzis, G., Gikas, G., Linker, R., Zoras, S., Evagelopoulos, V., Tsihrintzis, V., Battilani, A., & Sylaios, G. (2017). Operational precise irrigation for cotton cultivation through the coupling of meteorological and crop growth models. *Water Resources Management, 31*, 1547–1562. https://doi.org/10.1007/s11269-016-1548-7
44. *Xuân* Thảo, N., & Nhung, L. (2019). A novel multi-criteria decision making method for evaluating water reuse applications under uncertainty. *Vietnam Journal of Agricultural Sciences, 1*(3), 230-239. https://doi.org/10.31817/vjas.2018.1.3.04
45. Yilmaz, B., & Harmancioglu, N. (2010). Multi-criteria decision making for water resource management: A case study of the Gediz River Basin, Turkey. *Water SA, 36*, 563-576. https://doi.org/10.4314/wsa.v36i5.61990
46. Zadeh, L.A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

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مقاله پژوهشی

جلد ۳۸، شماره ۴، زمستان، ۱۴۰۳، ص. ۴۶۰-۴۴۳

تصمیم‌گیری گروهی ذینفعان بخش کشاورزی برای مدیریت پایدار منابع آب زیرزمینی: مطالعه موردی خراسان شمالی

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تاریخ دریافت: ۱۴۰۳/۰۹/۱۷

تاریخ پذیرش: ۱۴۰۳/۱۰/۲۹

چکیده

منابع آب زیرزمینی به‌عنوان یک منبع حیاتی برای کشاورزی در مناطق خشک محسوب می شوند که بردا شت بی‌رویه از آن‌ها منجر به چالش‌های جدی مانند کاهش سطح آب و افزایش کم‌آبی شده است. این مطالعه با تمرکز بر نیاز فوری به مدیریت پایدار منابع آب زیرزمینی، از رویکرد تصمیم‌گیری گروهی مشارکتی با حضور ذینفعان متنوع، به‌ویژه کشاورزان، استفاده می‌کند. نادیده گرفتن مشارکت کشاورزان در فرآیند تصمیم‌گیری منجر به سیا ست‌های ناکارآمد شده ا ست. این پژوهش با به‌کارگیری روش‌های تصمیم‌گیری چندمعیاره (MCDM)، به‌ویژه تکنیک‌های آنتروپی شانون فازی و TOPSIS فازی، راهبردهای کاهش مصرف آب زیرزمینی در منطقه صفی‌آباد شمال خراسان، ایران را اولویت‌بندی می‌کند. داده‌های کیفی حاصل از مصاحبه با ذینفعان، بینش‌هایی در مورد چالش‌ها و فرصت‌های مرتبط با استفاده از آب زیرزمینی ارائه می‌دهد و دو راهبرد اصلی را شناسایی می‌کند: (۱) انتقال به کشت محصولات کم‌آب‌بر و (۲) پذیرش سیستم‌های آبیاری مدرن. این راهبردها نه تنها کاهش قابل توجهی در مصرف آب را نوید می‌دهند، بلکه از شیوه‌های کشاورزی پایدار نیز حمایت می‌کنند. یافته‌ها بر اهمیت همکاری ذینفعان در اجرای سیاست‌های مؤثر مدیریت آب تأکید می‌کنند تا استفاده مسئولانه از منابع تضمین شده و پایداری بلندمدت حاصل شود. این مطالعه به‌عنوان الگویی برای پژوهش‌های آینده عمل می‌کند و از روش‌های ترکیبی که تحلیل‌های کیفی و کمی را ادغام می‌کنند، برای ارائه توصیه‌های سیاستی و بهبود مدیریت منابع آب حمایت می‌کند.

واژه‌های کلیدی: تصمیم‌گیری، راهبردهای حفاظت از آب، مدیریت آب کشاورزی، مشارکت ذینفعان، نقش کشاورزان

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https://doi.org/10.22067/jead.2025.91123.1320

Contents

Agricultural Economics & Development

(AGRICULTURAL SCIENCES AND TECHNOLOGY)

Vol. 38 No.4 2025

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.

P.O.BOX: 91775- 1163

Fax: +98 -0511- 8787430

E-Mail: Jead2@um.ac.ir

Web Site: https://jead.um.ac.ir/

Ferdowsi University of Mashhad

Journal of Agricultural Economics & Development

(Agricultural Sciences and Technology)

Vol.38 No.4

2025

ISSN:2008-4722

Contents