نشریه علمی

اقتصاد و توسعه کشاورزی

(علوم و صنایع کشاورزی)

جلد ۳۹ شماره ۲

سال ۱۴۰۴

شماره پیاپی ٦٧

شاپا: ۲۰۰۸-٤۷۲۲

عنوان مقالات

نابرابری‌های روستایی-شهری در تقاضای غذای حیوانی و زیان‌های رفاهی در ایران طی کووید-۱۹: رویکرد QUAIDS ۱۳۸
علیرضا کرباسی- سعید جلالیان

تأثیر سیاست‌های کشاورزی بر تاب‌آوری کشاورزان خرده مالک در برابر ناامنی غذایی در ایران ۱٤۹
شیرین ظریف مرادیان- محمود دانشور کاخکی- محمود صبوحی صابونی

بازاریابی دیجیتال محصولات کشاورزی: عوامل مؤثر بر تمایل مصرف‌کنندگان در ارومیه، ایران ۱٦٤
مرتضی مولائی- معصومه رشیدقلم- باقر حسین‌پور

ارزیابی همزمان کارایی فنی و ریسک تولید مزارع برنج ۱۸۰
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تعیین الگوی بهینه کشت با تأکید بر تعامل ریسک و سودآوری: اراضی کشاورزی دشت دهگلان ۱۹۲
مهسا قصابی- محمود حاجی رحیمی- حامد قادرزاده- راضیه شنگایی

تحلیل الگوی مصرف مواد غذایی در مناطق روستایی ایران: شناسایی استان‌های با مصرف استاندارد و همگن ۲۱۰
مهدی شعبانزاده خوشرودی

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 39 شماره 2 تابستان1404

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

صاحب امتیاز: دانشگاه فردوسی مشهد

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

مندرجات

نابرابری‌های روستایی-شهری در تقاضای غذای حیوانی و زیان‌های رفاهی در ایران طی کووید-19: رویکرد QUAIDS 138
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Journal of Agricultural Economics & Development

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

Research Article
Vol. 39, No. 2, Summer 2025, p. 117-138

Rural-Urban Disparities in Animal-Source Food Demand and Welfare Losses during COVID-19 in Iran: A QUAIDS Approach

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Received: 27-05-2024 Revised: 26-03-2025 Accepted: 22-04-2025 Available Online: 22-04-2025	**How to cite this article:** Karbasi, A., & Jalalian, S. (2025). Rural-urban disparities in animal-source food demand and welfare losses during COVID-19 in Iran: A QUAIDS approach. *Journal of Agricultural Economics & Development, 39*(2), 117-138. https://doi.org/10.22067/jead.2025.88095.1267

Abstract

The COVID-19 pandemic presented major global challenges, including a decline in per capita income growth across all income groups in 2020. The protein sector, particularly Animal-Source Foods (ASF) faced increased pressure on both supply and demand, resulting in price volatility. This study examines how income shocks affected food expenditure patterns and consumption behavior, with a focus on protein-rich ASF. Utilizing the QUAIDS model, budget data from Iranian households in rural and urban areas were analyzed for 2019 (pre-pandemic) and 2020 (during pandemic). The findings yield three key insights: (1) The average food expenditure share rose from 37% to 42%, with a sharper increase in rural areas; (2) Positive expenditure elasticities were observed across the six ASF groups including livestock meat, poultry, aquatic animal products, dairy, eggs, and fats, while own-price elasticities were relatively smaller; and (3) Welfare losses across ASF groups ranged from 2% to 24.2%, driven by policy imbalances, supply chain disruptions, and unequal utility distribution. Rural households experienced greater welfare losses in all ASF categories except fats. The study recommends targeted interventions: price-based support for urban areas and expanded social services for rural regions. To strengthen policy responses and enhance long-term food security, future research should assess the potential for substituting plant-based proteins as sustainable and cost-effective alternatives. These findings offer valuable guidance for policymakers aiming to improve nutritional resilience and economic stability in the post-pandemic era.

Keywords: Animal-source food (ASF), COVID-19, Iran, QUAIDS model, Welfare losses
JEL Classifications: D12, Q11

Introduction

The outbreak of COVID-19 triggered an unprecedented global crisis. The pandemic disrupted supply chains, reduced economic activity, and caused simultaneous demand and supply shocks that affected all sectors including the food system (Sarani *et al*., 2025). While no country was spared, the effects were uneven across regions, income groups, and sectors, revealing deep structural vulnerabilities in global economies. Scholars across disciplines from health and economics to sociology have documented these impacts and explored adaptive policy responses to mitigate long-term consequences. Their reports highlighted shifts in government food strategies, altered consumer behaviors, changes in household priorities, and even reductions in food waste, all of which reflect the profound impact of the

https://doi.org/10.22067/jead.2025.88095.1267

pandemic on how societies produce, distribute, and consume food (Ahmed & Sarkodie, 2021; Ceylan *et al*., 2020; Fan *et al*., 2021).

The pandemic simultaneously disrupted both the supply and demand sides of markets. On the supply side, firms faced operational pressures due to partial or total closures, labor shortages caused by quarantine measures, and financial constraints within supply chains (Aday & Aday, 2020). Qualitative and quantitative fluctuations in raw materials (Grinberga-Zalite *et al*., 2021) and restrictions on international trade further compounded these challenges (Hayakawa & Mukunoki, 2021). Meanwhile, the demand side experienced shifts in consumer behavior, with increased precautionary savings, panic buying, and changes in dietary preferences shaped by health concerns and reduced incomes (Anderson *et al*., 2021). These dual pressures severely tested the resilience of global food chains, with the protein sector, particularly animal-sourced foods (ASF), standing at the center of the disruption.

ASFs, encompassing livestock meat, poultry, aquatic animal products, dairy, eggs, and animal-derived fats, encounter a distinct array of nutritional and sustainability challenges. On one hand, demand for high-quality protein increased due to its perceived role in boosting immune function during a health crisis (Akaichi & Revoredo-Giha, 2014). On the other hand, fears surrounding virus transmission through meat products, increased production costs from new hygiene protocols, and rising consumer sensitivity to food safety and quality created complex demand dynamics. The result was an environment of heightened price volatility and uncertain supply. These changes were further amplified by global campaigns advocating plant-based alternatives and by misinformation regarding the virus's origins, which affected ASF consumption trends (Tonsor *et al*., 2023).

Despite such challenges, protein remains a critical dietary component, especially during the pandemic. Adequate protein intake is essential for maintaining immune defense, reducing vulnerability to infections, preserving muscle mass, and ensuring proper metabolic function (Iddir *et al*., 2020). Protein deficiencies, particularly in low-income populations, can compromise immune response and elevate the risk of infectious diseases (Rodríguez *et al*., 2011). Globally, protein availability improved significantly between 2000 and 2017, with developing regions such as Asia, Africa, and Latin America experiencing above-average growth in protein supply (Fig. 1) (FAO, 2020a). While plant-based proteins remain dominant in many regions accounting for 78% of protein sources in Africa and 66% in Asia, the share of animal-origin proteins continues to rise worldwide, reflecting shifting dietary preferences and nutritional priorities. ASFs are recognized as a premier source of high-quality, nutrient-rich food, particularly for vulnerable populations such as children aged 6-23 months (WHO, 2014).

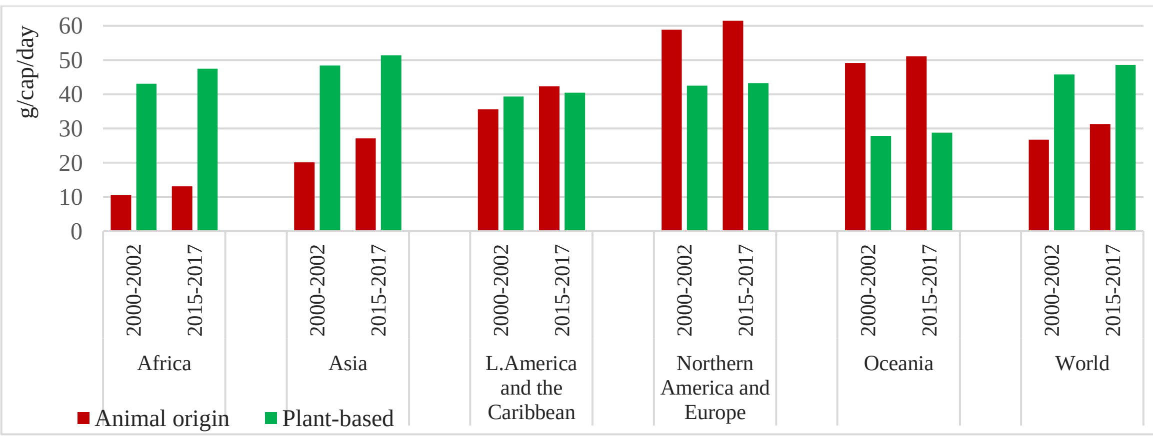

Figure 1- Average protein supply by region and origin
Source: FAOSTAT (2020a)

Nevertheless, the affordability and accessibility of ASF are highly sensitive to income changes. Classical microeconomic theory, particularly Engel's law, provides insight into how income shifts affect food consumption patterns. Engel (1857) observed that as income increases, the proportion of income spent on food declines, and vice versa. This principle remains critical in explaining household food behavior, especially during economic downturns. When incomes decline sharply as they did during the pandemic, households often increase the share of their budget allocated to food, potentially shifting consumption away from higher-value ASFs toward cheaper alternatives. In low-income (LI) and middle-income (MI) countries, demand for ASFs is more income-elastic, reflecting their perception as luxury items that are consumed less frequently (Gao, 2012). As income rises, consumers allocate a smaller budget share to food, consistent with Engel's Law, which states that the proportion of income spent on food decreases with increasing household income. This shift can lead to higher food consumption and changes in dietary composition, favoring more value-added and protein-rich products. According to FAO report from 2000 to 2017, the share of ASFs by weight was 29% in high-income countries, 20% in upper and lower-middle-income (LMI) countries, and 11% in LI countries (FAO, 2020b). Consequently, a decline in per capita income has negatively impacted ASF consumption. Therefore, fluctuations in income significantly influence dietary patterns and the substitution between staple foods and higher-value products.

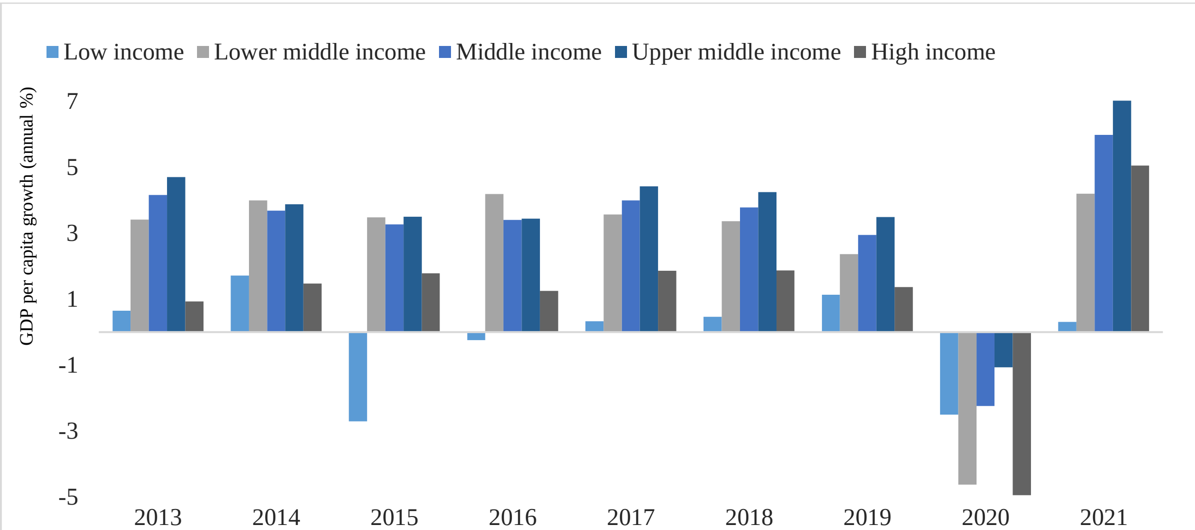

Figure 2- Annual percentage growth rate of GDP per capita based on constant local currency

Source: (*World Development Indicators|DataBank*, n.d.)

The global economic contraction induced by COVID-19 sharply illuminated disparities across income groups (Fig. 2). In 2020, all income brackets recorded negative per capita income growth, with high-income (HI) countries experiencing the most pronounced decline, driven by service sector disruptions from lockdowns. Upper-middle-income (UMI) countries, which boasted the highest GDP per capita growth in 2019, were unprepared for the crisis, their reliance on trade-sensitive industries and constrained fiscal capacity amplifying the shock. LI countries, despite marginal growth of 0.3% in 2021, struggled with structural weaknesses and inadequate policy responses, reversing pre-2020 gains. The pandemic underscored LI nations' vulnerability to external shocks, worsened by deficient healthcare systems and fiscal limitations. Recovery trajectories diverged significantly:

UMI economies capitalized on resilient sectors and supply chain adaptability, while HI countries stabilized more rapidly. Conversely, LI and select UMI nations faced protracted challenges. In developing countries like Iran, diminished purchasing power triggered nutritional trade-offs, intensifying inequalities in access to ASF and exposing food security fragilities. As a "great disruptor," COVID-19 magnified pre-existing economic disparities, highlighting the urgent need for targeted policy frameworks to bolster resilience in LI and UMI contexts, where economic fragility remains a persistent barrier to recovery.

Research Background

The COVID-19 pandemic officially reached Iran on February 19, 2020, and by March 4, it had spread to all provinces. Nationwide vaccination began on February 9, 2021, but the sixth wave, triggered by the Omicron variant, continued until March 2022. The first day without a COVID-19 death was recorded on June 2, 2022. From 1987 to 2019, Iran was a LMI country for 19 years and an UMI country for 14 years, maintaining its UMI status since 2009 (GDP per capita: $4,046–$12,535). However, the Iranian economy faced significant challenges with growth rates of 3.8%, -4.7% and -8.2% in 2017, 2018 and 2019 respectively. Despite the continuous population growth, the national income decreased by 60%, from $444 billion in 2017 to $191 billion in 2020. Table 1 shows the economic situation of Iran in the two years of the study.

Table 1- Economic growth and inflation in Iran.

Years	Season	GDP Annual Growth Rate (Constant 2016)	Inflation rate
2019 pre-pandemic	Q1	-6.4	4
	Q2	-2.9	6.7
	Q3	5.1	21.6
	Q4	3.8	17
2020 during pandemic	Q1	7.9	9.8
	Q2	6.5	10
	Q3	1	12
	Q4	3.9	10

Source: Statistical Center of Iran

Urban residents comprise 76% of Iran's population, and rapid urbanization has changed feeding habits and increased demand for livestock products. In 2019, per capita consumption of livestock products was 133 kg, with dairy products accounting for 90% (121.08 kg) and red meat for 12.04 kg. Iran's poultry industry, which has a 140-year history, ranks 11th and 19th in the world in terms of chicken and egg production. In 2019, the per capita consumption of chicken and eggs was 28 kg and 11 kg respectively, reflecting their importance in the Iranian food supply chain.

The COVID-19 pandemic placed additional strain on the protein supply chain, resulting in price increases for animal source foods (ASF) (Fig. 3). The most significant price surges were observed in red meat and butter, while prices for milk, eggs, chicken, and cheese rose more gradually and with some delay. Butter prices rose sharply due to Iran's reliance on imports of semi-finished products. ASF and cereals, bread, flour and pasta account for over 53% of Iran's basket of goods, with both groups recording a slight increase in 2020. The cereals group saw the largest increase, while vegetables and pulses declined, likely due to hygiene concerns in the vegetable supply chain. The consumption of fruits and nuts increased, which can be attributed to the quarantine conditions.

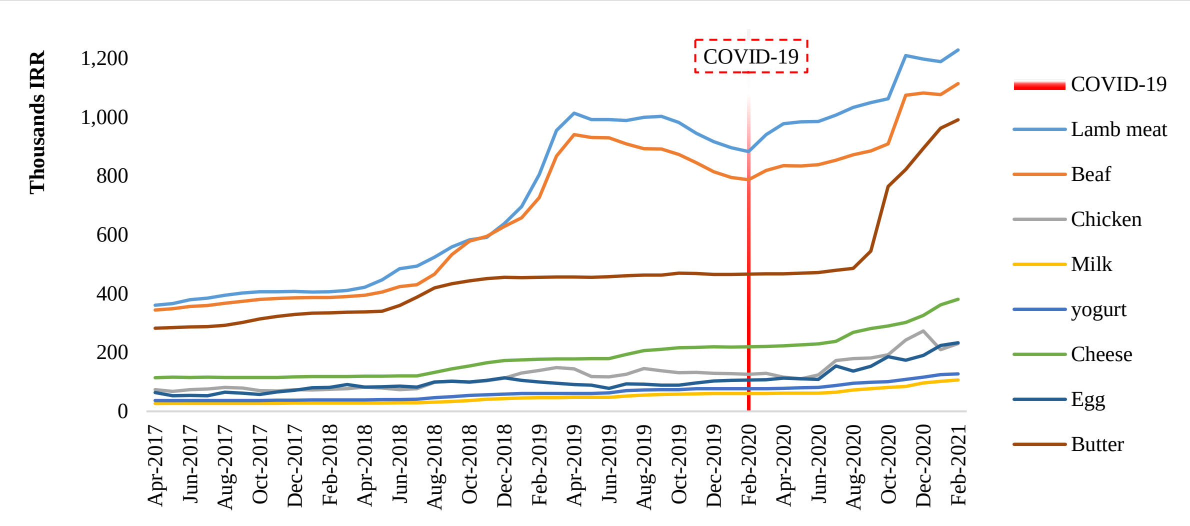

Figure 3- The Average price of selected food items in urban areas of Iran (IRR)
Source: Statistical Center of Iran

Fig. 4 shows that ASF and cereals, bread, flour and noodles account for more than 53% of Iran's basket and both will increase slightly in 2020. Cereals recorded the highest increase, while vegetables and pulses declined, likely due to hygiene issues in the supply chain. The consumption of fruit and nuts increased during the quarantine. Overall, the pandemic has disrupted the Iranian food supply chain, leading to dietary changes and price fluctuations, especially for ASF.

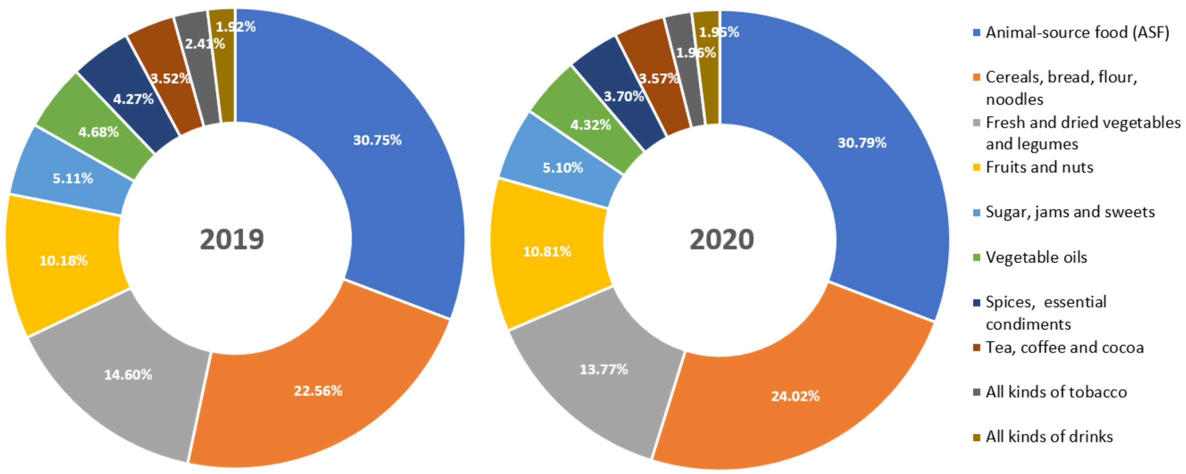

Figure 4- Expenditure share of household food consumption: 2019-20
Source: Author's own compilation

This study investigates the impact of the COVID-19 pandemic on the expenditure share and consumption patterns of ASF in Iranian households, focusing on the interplay between declining per capita income and rising food prices. ASF, encompassing livestock meat, poultry, aquatic products, dairy, eggs, and animal-derived fats, are prioritized due to their high-quality protein and essential micronutrients (e.g., iron, zinc, vitamin B12), which are critical for health, particularly during the disease outbreak crisis. Unlike plant-based proteins, ASF offer complete amino acid profiles and higher bioavailability, but their higher cost and vulnerability to supply chain disruptions make them a key focus for assessing food security risks in MI countries like Iran. The main research question of this study is: How economic and health-related shocks from the pandemic have affected household budget allocation and ASF consumption? The study addresses this by analyzing shifts in food demand, driven by reduced purchasing power and heightened awareness of immune-boosting diets. This research is vital for understanding the short-term effects of the pandemic on food demand and welfare, as inadequate ASF intake can weaken immune systems, exacerbating vulnerabilities (Batlle-Bayer *et al*., 2020). By examining these dynamics, the study aims to inform policies that mitigate nutritional deficits and enhance household welfare.

The research employs the Quadratic Almost Ideal Demand System (QUAIDS) model to analyze household budget data from 2019 (pre-pandemic) and 2020 (during pandemic) across rural and urban areas in Iran, a country facing additional economic pressures from sanctions and inflation. The QUAIDS model estimates price and income elasticities for six ASF categories, capturing how households prioritize food during economic shocks. Additionally, the study calculates welfare losses using compensating variation (CV) and compensated (Hicksian) price elasticities, offering a robust framework to assess the pandemic's economic impact. By distinguishing between rural and urban households, the analysis highlights regional disparities in food demand and welfare losses, providing nuanced insights into the uneven effects of the crisis.

The results underscore the need for targeted interventions to address nutritional gaps, particularly for vulnerable populations. Furthermore, the study prompts consideration of sustainable protein alternatives, such as plant-based options, in future food resilience strategies. By providing empirical evidence on the pandemic's disruption of food demand in Iran, this research fills a critical gap in the literature. Its policy-relevant insights support the development of regionally tailored interventions to mitigate nutritional risks and welfare losses. The findings are particularly timely given global economic and health disruptions, contributing to the broader goal of ensuring access to nutrient-rich diets and enhancing food security for diverse populations.

Literature review

The emergence of new coronavirus variants is being observed in many countries, especially in developing countries such as Iran, which are still facing challenges. Due to the limited data available in these countries, there have been few studies analyzing the changes in food demand under pandemic conditions. Most of them have also used the QUAIDS model and found it useful.

Coelho *et al*. (2010) estimated a QUAIDS for 18 food products using data from a Brazilian Household Budget Survey for the years 2002 and 2003. They showed that purchase probabilities of staple foods were negatively related to family monthly income, while meat, milk, and other products showed a positive relation. They also find that regional, educational, and urbanization variables are also important.

Khoiriyah *et al*. (2020) analyzed the impact of the price change, income, and household size on the demand for five commodity groups, i.e. eggs, chicken, beef, fish, and powder milk in the Indonesian National Socio-Economic Survey 2016. They used 291,414 data from households in Indonesia which were analyzed by QUAIDS. The result showed that all of the price elasticity was negative and the income elasticity was positive.

Nicola *et al*. (2020) summarized the socio-economic effects of COVID-19 on individual aspects of the world economy. They showed that the need for commodities and manufactured products has decreased and the food sector is also facing increased demand due to panic-buying and stockpiling of food products.

Poudel *et al*. (2020) reviewed the possible impacts of the global pandemic COVID-19 on Food and Agriculture across the globe. They pointed the pandemic protocols and provisions interfere with the supply chain of the market with impaired production and distribution accompanied by a lack of labor and supply of inputs. This vastly affects livestock, poultry, fishery as well as dairy production.

Khan *et al.* (2021) reviewed COVID-19's effects on the agricultural sectors. They showed COVID-19 affects the profit of agriculture, livestock, and fisheries and has opened up inequalities within the food chain. As a result, the epidemic has shown that the food chain is fragile.

Vargas-Lopez *et al.* (2022) examined how household culinary traditions and food management have changed in Mexico as a result of COVID-19-related restrictions, and their impact on food waste. The results show that the participating households increased their monetary expenditure on groceries and reduced food waste during the pandemic. The estimation of consumer responsiveness to waste, through the introduction of a framework based on QUAIDS, confirmed that, even more during the lockdown, food waste has become a luxury good.

Kaicker *et al.* (2022) examined covariates of food security and the impact of COVID-19-induced shocks, among households in India using a nationally representative survey. Using a 2SLS panel regression model, found an important role of incomes, relative food prices, household characteristics, as well as mobility restrictions in response to the rising number of infections in a given region in explaining varying food expenditure shares before and during the COVID-19 pandemic.

The literature highlights the significant impact of economic and health crises, such as COVID-19, on food demand and consumption patterns across various countries. Coelho *et al.* (2010) and Khoiriyah *et al.* (2020) demonstrated the effectiveness of the QUAIDS model in analyzing food demand, showing how income, prices, and household characteristics influence consumption. Nicola *et al.* (2020) and Poudel *et al.* (2020) emphasized the pandemic's disruption of food supply chains and increased demand for essential goods. Khan *et al.* (2021) and Kaicker *et al.* (2022) further illustrated how COVID-19 exacerbated inequalities in food security and altered household expenditure. Vargas-Lopez *et al.* (2022) explored changes in food management and waste during the pandemic. Collectively, these studies underscore the need for robust models like QUAIDS to understand and address food demand shifts during crises.

Material and Methods

QUAIDS Methodology

Structural econometric modeling, in contrast to non-structural modeling, that lacks economic theoretical foundations, is based on economic theories and takes into account the theoretical relationships between the dependent variable and the explanatory variables. A large proportion of demand models are based on consumer behavior and the maximization of total utility. Several structural models have been presented in the literature. Linear Expenditure System (LES) (Stone, 1954), Rotterdam Model (Barten, 1969), Translog System (Christensen *et al.*, 1973), Indirect Transfer System (ITS) (Christensen *et al.*, 1975), Quadratic Expenditure System (QES) (Pollak & Wales, 1978), Almost Ideal Demand System (AIDS) (Deaton & Muellbauer, 1980), all of which have attempted to provide more flexible systems and adapt theories to experimental studies. More recently, the most popular approach, especially in the food field, has been the Quadratic Almost Ideal Demand System (QUAIDS). Aiming at a more flexible performance and a nonlinear Engel curve coverage more in line with reality, the QUAIDS was introduced by Banks *et al.* (1997). QUAIDS shows the non-linear responses of price and expenditures changes to demand and provides an estimate of a higher order between consumption of goods and income (Engel curve). The QUAIDS model is derived from an indirect utility function that has the following form Equation ((1):

$$Ln\,V(P,m) = \left[\left\{\frac{\ln m - \ln a(P)}{b(P)}\right\}^{-1} + \lambda(P)\right]^{-1} \quad (1)$$

Where:

1) $\ln a(P) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln p_i + 1/2 \sum_{i=1}^{k} \sum_{j=1}^{k} \gamma_{ij} \ln p_i \ln p_k$

2) $b(P) = \prod_{i=1}^{k} p_{i=1}^{\beta_i}$
3) $\lambda(P) = \sum_{i=1}^{k} \lambda_i \ln p_i$

The index i stands for the number of goods in the demand system, P is the price of good i, m is the total expenditure, (1) is the translog expansion and (2) is the Cobb-Douglas price aggregator. (3) The household expenditure function is similar to AIDS when $\lambda = 0$. Using Roy's identity in equation ((1), the share equations can be written as follows equation ((2):

(2)

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + \beta_i \ln\left(\frac{m}{a(P)}\right) + \frac{\lambda_i}{b(P)}\left[\ln\left(\frac{m}{a(P)}\right)\right]^2$$

s.t:
1) $\sum_{i=1}^{k} w_i = 1$
2) $\sum_{i=1}^{k} \alpha_i = 1$
3) $\sum_{i=1}^{k} \beta_i = 0$
4) $\sum_{i=1}^{k} \lambda_i = 0$
5) $\sum_{i=1}^{k} \gamma_{ij} = 0$
6) $\gamma_{ij} = \gamma_{ji}$

To align with economic theory and limit the number of parameters to estimate, certain restrictions are imposed. The *Restriction (Rst.) 1* to *5* refer to the Adding-up condition. *Rst.5* refers to the homogeneity condition and *Rst.6* refers to the Slutsky symmetry condition. The method introduced by Ray (1983) and further developed by Poi (2002) is used to take demographic characteristics into account. In this method, z is defined as a representative vector of household demographic characteristics. If $e^R(P,u)$ is the expenditure function of the reference household, the expenditure function for each household has the form of $e(p,z,u) = m_0(p,z,u) \times e^R(p,u)$. The function m_0 scales the expenditure function to take into account the household characteristics. Roy decomposes a scalar function in the form $m_0(p,z,u) = \overline{m}_0(z) \times \emptyset(p,z,u)$, where the first term measures the increase in a household's expenditure as a function of z. The second term controls for changes in relative prices and goods actually consumed. Equation ((3) shows the equations for the expenditure shares taking z into account:

(3)

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + (\beta_i + \eta_i') \ln\left(\frac{m}{\overline{m}_0(z)a(P)}\right) + \frac{\lambda_i}{b(P)c(P,z)}\left[\ln\left(\frac{m}{\overline{m}_0(z)a(P)}\right)\right]^2$$

Where:

$$\mathrm{c(P,z)} = \prod_{j=1}^{k} p_j^{\eta_j' z}$$

$$\sum_{j=1}^{k} \eta_{rj} = 0 \; for \; r = 1, \dots, s.$$

η_j' represents the j-th column of the parameter matrix $\eta_{s\times k}$. *Rst.2* should be considered for the Adding-up condition. Different approaches have been used to estimate equation (3). Banks *et al*. (1997) proposed a two-step GMM method for estimating the system of nonlinear equations to account for the endogeneity and nonlinearity of the regressions. Poi (2008) proposed a nonlinear seemingly unrelated regression (NSUR) method. The NSUR approach was followed in this study. By partially differencing equation (3) in the form $\mu_i = \partial w_i / \partial \ln m$ and $\mu_{ij} = \partial w_i / \partial \ln p_j$, the expenditure elasticity e_i in equation (4) and uncompensated price elasticities (Marshallian) e_{ij}^u in equation (5) are obtained. Using these values and the Slutsky equation, the compensated price elasticity can be estimated (Hicksian) e_{ij}^c using equation ((6). δ_{ij} is Kronecker delta, which is equal to one if $j = 1$ and zero otherwise.

(4)

$$e_i = \frac{\mu_i}{w_i} + 1$$

(5)

$$e_{ij}^u = \frac{\mu_{ij}}{w_i} - \delta_{ij}$$

(6)

$$e_{ij}^c = e_{ij}^u + e_i w_j$$

Welfare Change Indicator

Understanding changes in welfare requires the use of welfare change indicators such as compensating variation (CV), which have been used in many studies related to the food sector, e.g. in Adekunle *et al*. (2020) and Mokari-Yamchi *et al*. (2022). CV is the monetary compensation required to bring the consumer back to the original utility level after the price change (Araar & Verme, 2016). The CV can be written as the difference between two values of the cost function (Equation (7); where $e(U, P)$ is the expenditure function, P is the vector of prices and U is the utility. These changes are measured by the level under the compensated demand curve (Hicksian) following an economic change such as the economic impact of COVID-19.

$$CV = e(U_0, P_1) - e(U_0, P_0) \tag{7}$$

Using a second-order Taylor series and Shephard's lemma for equation ((7), the impact of price changes on the consumer is obtained (Badolo & Traoré, 2015):

$$\frac{CV}{x_0} \cong \frac{p_{0,i}q_i(p_0,x_0)}{x_0}\frac{\Delta p}{p_{0,i}} + \frac{1}{2}e_i\frac{p_{0,i}q_i(p_0,x_0)}{x_0}\left(\frac{\Delta p}{p_{0,i}}\right)^2 \tag{8}$$

Where q_i and p_i are the quantity demanded and food group price respectively. x_0 is the ASF expenditure and e_i is the Hicks own-price elasticity of demand for a particular food group.

Data

The data for the estimation of equations 3 to 8 come from the Iran Households Expenditure and Income Survey (IHEIS), which has been conducted annually by the Statistical Center of Iran (SCI) since 1935. The survey, which balances urban and rural households, covers 31 provinces and includes data from 38,099 households in 2019 (pre-pandemic) and 37,294 households in 2020 (during pandemic). The questionnaire comprises four sections: social characteristics of the household, information on place of residence, expenditure on food and other goods and household income. In the food expenditure section, over 630,000 observations were collected for 228 food items, including 58 ASF, which were categorized into six groups (Table 2). Nominal food consumption was calculated on the basis of retail prices, with values recorded monthly.

Table 2- ASF items in the IHEIS questionnaire

ASF group title	Scope
Livestock meat	The meat of *sheep*, *goat*, and *yeanling*. *Calf* and organ meats Other bushmeats, cured meats, sausage, Cold meats Meat cans, cured meats, precooked meats including hamburgers, kebab steak, and so on.
Poultry meat	*Hen*, *rooster*, *chicken*, *ostrich*, *turkey*, *goose*, *duck*, *quail*, and *hunting* birds Other birds, their offal. and bird meat cans Ready to cook meats such as chicken barbecue schnitzel and…
Aquatic meat	Fresh and frozen fish, smoked and salted fish Different fish cans, fresh frozen and cured *shrimp* *Oysters* & *Caviar* Other types of ready-to-cook Fish
Dairy products	Kinds of milk, milk powder, and milkshake Creams, kinds of ice creams, yogurt, dough, cheese, *pietra cheese*, and kinds of whey Kinds of mixed cheese, and *Nagorno qrvt*
Eggs	Local and industrial eggs *Duck*, *goose*, *turkey*, and others
Animal-derived Fats	Kinds of animal oil, fat, and tallow Pasteurized and unpasteurized animal butter

Source: Extracted from the IHEIS questionnaire

Due to the high proportion of informal economic activities, shadow activities (Angrist *et al.*, 2021), and self-employment in developing countries, total household demand was considered as income. Total household demand is calculated from the sum of expenditure on food and beverages, clothing, housing, health, communication and transportation, culture and leisure, education, durable goods and investment based on the data in Part3 of the questionnaire. For a more detailed analysis, the demographic variables of household size and residential status of the household were used as dummies (rural=1/urban=0).

Results

The results of the analysis include descriptive analysis, estimated elasticities, and welfare losses based on data and parameters. Stata/MP14.0 software was used for statistical analysis.

Descriptive Statistics

The descriptive statistics section provides an overview of the key variables and their distribution of the dataset. This analysis offers insights into household expenditure patterns, particularly for ASF, across urban and rural areas in Iran before and during the COVID-19 pandemic. Table 3 and Fig. 5 summarize the mean, standard deviation, and other relevant statistics, highlighting the changes in consumption and expenditure trends over the study period.

Table 3- Summary table of sample characteristics for datasets

Variables	2019 pre-pandemic			2020 during pandemic		
	All	**Urban**	**Rural**	**All**	**Urban**	**Rural**
Households	38,099	19,793	18,306	37,294	19,178	18,116
Population ratio (%)		52.0	48.0		51.4	48.6
Household size (Mode)	3.46 (4)	3.43 (4)	3.49 (4)	3.43 (4)	3.40 (4)	3.47 (4)
Age of household head in years	51.5	50.9	52.1	51.8	51.5	52.2
Median age in years	32	32	33	33	32	33
Female-headed household (%)	14	13	15	15	14	15
Ratio of food expenditure (%)	37.87	34.25	41.79	42.08	31.37	53.41
Ratio of Non-Animal food expenditure (%)	69.25	68.47	70.08	69.21	68.39	70.08
Ratio of Animal food expenditure (%)	30.75	31.53	29.92	30.79	31.61	29.92
Expenditure share on livestock meat (%)	20.79	23.01	18.40	21.76	24.08	19.31
Expenditure share on poultry meat (%)	32.27	29.84	34.90	31.84	29.57	34.24
Expenditure share on aquatic meat (%)	5.55	6.16	4.90	5.19	5.71	4.63
Expenditure share on dairy products (%)	29.37	29.67	29.05	27.78	27.93	27.61
Expenditure share on eggs (%)	9.48	8.62	10.41	11.10	10.21	12.05
Expenditure share on Animal-derived Fats (%)	2.53	2.70	2.35	2.34	2.50	2.16
Price of livestock meat (IRR)	667,813	683,496	650.857	820,001 (23%↑)	845,719 (24%↑)	792,775 (22%↑)
Price of poultry meat (IRR)	127,688	128,249	127,080	189,620 (49%↑)	190,864 (49%)	188,304 (48%↑)
Price of aquatic meat (IRR)	417,519	419,092	415,818	582,488 (40%↑)	599,873 (43%↑)	564,084 (36%↑)
Price of dairy products (IRR)	112,630	116,114	108,863	165,240 (47%↑)	171,474 (48%↑)	158,640 (46%↑)
Price of eggs (IRR)	97,069	94,742	99,586	164,749 (70%↑)	161,838 (71%↑)	167,831 (69%↑)
Price of Animal-derived Fats (IRR)	463,726	463,054	464,452	701,863 (51%↑)	703,109 (52%↑)	700,544 (51%↑)

Source: Author's own compilation

The demographic characteristics of households remained relatively consistent between 2019 and 2020. The most common household size was four members, and the average age of the household head was 51 years, with a marginal increase of 0.7% in 2020. The median age of the statistical population was 33 years, aligning closely with the global median age of 31.7 years reported by Worlddata.info, which ranks Iran 60th globally. Female-headed households accounted for 14% in 2019, rising slightly to 15% in 2020, reflecting a modest shift in household dynamics.

A significant change was observed in the share of food expenditure, which increased from 37% in 2019 to 42% in 2020. This rise was particularly pronounced in rural areas, where food expenditure surged from 41% to 53%, likely driven by economic pressures exacerbated by the COVID-19 pandemic. In contrast, urban households experienced a 2% decrease in the share of food expenditure. This divergence can be attributed to differing economic vulnerabilities and access to resources between urban and rural populations. The increase in food expenditure aligns with the decline in GDP per capita, as illustrated in figure Source: , which reflects the broader economic contraction during the pandemic.

In 2019, an average of 30.75% of total food expenditure was allocated to ASF, with urban households spending 2% more on ASF than rural households. Despite the overall increase in food expenditure by 5% in 2020, the share of ASF remained stable at 30.7%. This stability occurred despite significant price hikes across ASF categories, ranging from a 22% increase for livestock meat in rural areas to a 71% surge for eggs in urban areas. These price increases are consistent with global trends highlighted by studies such as Akter (2020) and Bai *et al.* (2022), which noted a widespread rise in food prices following the onset of the pandemic.

The persistence of ASF expenditure share, despite rising prices, suggests that ASF remains a critical component of the Iranian diet, with households prioritizing these foods even under economic strain. This finding underscores the importance of ASF in the food security and dietary patterns of Iranian households, particularly in the context of economic shocks. The data also highlights the resilience of food consumption patterns in the face of price volatility, as households adjusted their budgets to maintain access to essential food groups. Overall, these trends reflect the complex interplay between economic conditions, food prices, and consumption behavior during the COVID-19 pandemic.

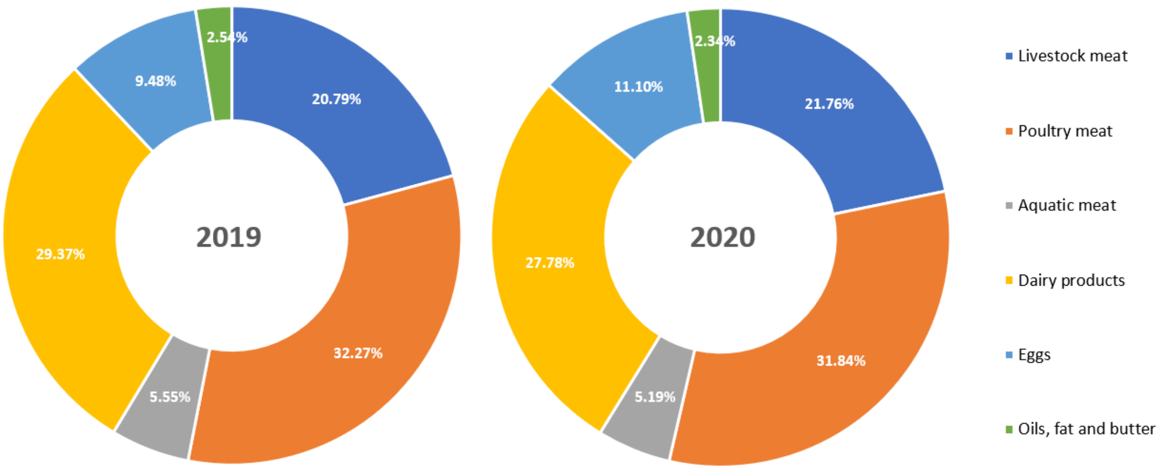

Figure 5- Expenditure share of household ASF consumption: 2019-20
Source: Author's own compilation

Fig. 5 graphically shows that the poultry group constitutes the largest share of ASF. The group of eggs increased the most, and the group of dairy products decreased the most. The details show that it was the same in rural and urban areas.

QUAIDS Estimation for the Whole Sample

The coefficients of the quadratic term (λ_i) in the QUAIDS model were statistically significant for all six food groups (P<0.001), underscoring the superiority of the QUAIDS model over the simpler AIDS model in capturing the nonlinear relationship between expenditure and food demand. Notably, the λ value for the aquatic meat group was closer to zero compared to other groups, suggesting a less pronounced quadratic effect in this category. Tables 4 and 5 present the estimated expenditure elasticities, as well as compensated and uncompensated price elasticities derived from the QUAIDS analysis. Across both years (2019 and 2020), expenditure elasticities were positive for all food groups, indicating the absence of inferior goods. In 2019, the elasticities ranged from 0.33% to 1.90%, while in 2020, they ranged from 0.37% to 1.88%. The groups of livestock, aquatic products, and fats exhibited elasticity values greater than one, classifying them as luxury goods. This implies that consumption of these groups is highly sensitive to income changes, and households are more likely to reduce their consumption of these items during economic downturns.

In Iran, where approximately 71% of cooking fats used in frying are solid vegetable fats (Salehzadeh *et al*., 2019), the classification of animal fats as luxury goods aligns with dietary patterns and preferences. Other food groups, such as eggs and poultry meat, displayed positive expenditure elasticities below unity, categorizing them as necessity goods. Eggs, in particular, exhibited the lowest elasticity, reflecting their essential role in Iranian diets. Poultry meat, with an elasticity closer to one, behaved more like a normal good, indicating a more proportional response to income changes compared to other groups. Overall, the QUAIDS model provides a nuanced understanding of food demand in Iran, revealing how income fluctuations differentially impact the consumption of luxury and necessity goods, particularly during periods of economic stress.

The primary diagonal of the matrices presented in Tables 4 and 5 delineates the own-price elasticities, which, as anticipated by theoretical frameworks, exhibit all negative values. The magnitude of these values inversely correlates with the relative significance of each food group among households. Analysis of the data reveals that eggs registered the lowest Hicksian elasticity at -0.34, a figure that remained unchanged in 2020. In 2019, per capita egg consumption in Iran was recorded at 8.33 kg, reflecting a 0.483 percent increase from the previous year. In a global context, Iran is ranked 73rd out of 161 countries regarding per capita egg consumption, as reported by FAO (2020b). While aquatic meat is recognized as an excellent source of protein and omega-3 fatty acids, it is perceived as a luxury item within the dietary preferences of Iranian households.

Based on the own-price elasticities, it was found that the demand for aquatic meat and animal fats was particularly sensitive to price fluctuations. The compensated own-price elasticity for fats in 2019, solely indicating the substitution effect, was measured at -1.14, categorizing it as a product with price-elastic demand. In contrast, the groups associated with eggs and poultry meat exhibited a lower sensitivity to price changes. With the exception of aquatic meat (-2.59) and fats (-1.14), the remaining groups were categorized as having own-price inelastic demand, as their elasticity values fell below one when responding to respective price alterations. It is notable that the own-price elasticity for the fats category experienced a substantial increase in 2020, escalating from -1.14 to -1.72.

The principal diagonal of the matrices in Tables 4-3 and 5-3 illustrates the uncompensated own-price elasticities (Marshallian), which account for the income effects of price changes and are generally larger than their compensated counterparts. A comparative analysis of the uncompensated values between 2019 and 2020 highlights an increase for livestock meat, rising from -0.86 to -1. In contrast, the dairy group remained unchanged at -0.89. Additionally, the values denoted as e_{ij} in the matrices of Tables 4 and 5 represent cross-price elasticities. The variation in the signs of certain values indicates that some food items are substitutes for one another, while others complement each other.

QUAIDS Estimation for the Subsample

Within the span of a single year, the proportion of food expenditure in rural regions rose from 41.79% to 53.41%, whereas in urban regions, this proportion shifted from 34% to 31% (Fig. 6). This pattern may be attributed to the phenomenon that, in addition to previous outlays, urban households have allocated part of their income towards preventive and therapeutic health measures. Conversely, rural households, facing diminished income, have concentrated their efforts on sustaining their nutritional intake. The analysis conducted using the QUAIDS model yields moderate evidence countering the significant hypothesis regarding the demographic characteristics associated with residential status (P-Value=0.07). Nevertheless, with a diminished level of confidence, the estimated parameters for both urban and rural settings were scrutinized. Estimates of elasticities for the years 2019-20 are presented in Tables 6 and 7.

Table 4- Whole sample: pre-pandemic (2019)

	L. meat	P. meat	A. meat	Dairy	Eggs	A.Fats
4-1: Expenditure elasticity						
	1.90	0.77	1.52	0.68	0.33	1.44
4-2: Hicksian (Compensated)						
L. meat	-0.47	0.12	0.019	0.27	0.02	0.02
P. meat	0.08	-0.63	0.17	0.25	0.06	0.05
A. meat	0.07	1.01	-2.59	0.94	0.33	0.22
Dairy	0.19	0.27	0.17	-0.69	0.01	0.03
Eggs	0.05	0.22	0.19	0.03	-0.34	-0.16
A.Fats	0.18	0.70	0.49	0.37	-0.61	-1.14
4-3: Marshallian (uncompensated)						
L. meat	-0.86	-0.49	-0.08	-0.28	-0.15	-0.02
P. meat	-0.07	-0.87	0.13	0.02	-0.008	0.036
A. meat	-0.24	0.52	-2.68	0.49	0.188	0.18
Dairy	0.05	0.05	0.14	-0.89	-0.05	0.01
Eggs	-0.1	0.11	0.17	-0.06	-0.37	-0.17
A.Fats	-0.11	0.23	0.41	-0.04	-0.75	-1.17

Source: Author's own compilation

Table 5- Whole sample: during pandemic (2020)

	L. meat	P. meat	A. meat	Dairy	Eggs	A.Fats
5-1: Expenditure elasticity						
	1.88	0.76	1.50	0.68	0.37	1.56
5-2: Hicksian (Compensated)						
L. meat	-0.59	0.18	0.08	0.28	0.02	0.01
P. meat	0.12	-0.49	0.07	0.19	0.05	0.04
A. meat	0.35	0.47	-2.54	0.99	0.35	0.35
Dairy	0.22	0.22	0.18	-0.70	0.02	0.04
Eggs	0.05	0.14	0.16	0.06	-0.34	-0.08
A.Fats	0.12	0.63	0.79	0.55	-0.38	-1.72
5-3: Marshallian (uncompensated)						
L. meat	-1.00	-0.41	-0.01	-0.23	-0.18	-0.03
P. meat	-0.03	-0.74	0.03	-0.02	-0.03	0.02
A. meat	0.02	-0.0007	-2.61	0.57	0.18	0.32
Dairy	0.07	0.003	0.15	-0.89	-0.05	0.03
Eggs	-0.02	0.02	0.14	-0.04	-0.38	-0.09
A.Fats	-0.21	0.13	0.71	0.12	-0.56	-1.76

Source: Author's own compilation

The analysis of Tables 6 and 7 offers key insights into the consumption behavior of rural and urban households before and during the COVID-19 pandemic. In 2019, rural households demonstrated greater sensitivity to income changes than their urban counterparts, as indicated by a wider range of expenditure elasticities across ASF groups, varying from 0.27 to 2.03. This disparity narrowed in 2020, likely reflecting the economic disruptions caused by the pandemic. Rural households also demonstrated higher sensitivity to price changes, with Hicksian price elasticities for ASF groups showing steeper values in rural areas (e.g., -0.38 for eggs to -2.82 for aquatic meat) compared to urban regions.

A notable observation is the stability of dairy product price elasticity (-0.69) for both rural and urban households during the pandemic, suggesting consistent demand patterns despite the crisis. Conversely, livestock meat and fat groups experienced increased price elasticity in both regions, with rural areas witnessing a more pronounced shift (e.g., fat group elasticity rising from -1.15 to -1.78 in rural areas versus -1.12 to -1.67 in urban areas). This heightened sensitivity underscores rural households' vulnerability to price fluctuations. Meanwhile, poultry and aquatic meat groups showed decreased price elasticity in both regions, indicating reduced responsiveness, possibly due to altered consumption priorities during the pandemic. These findings highlight the differential impacts of economic shocks on rural and urban households, emphasizing the need for targeted policy interventions to address rural vulnerabilities.

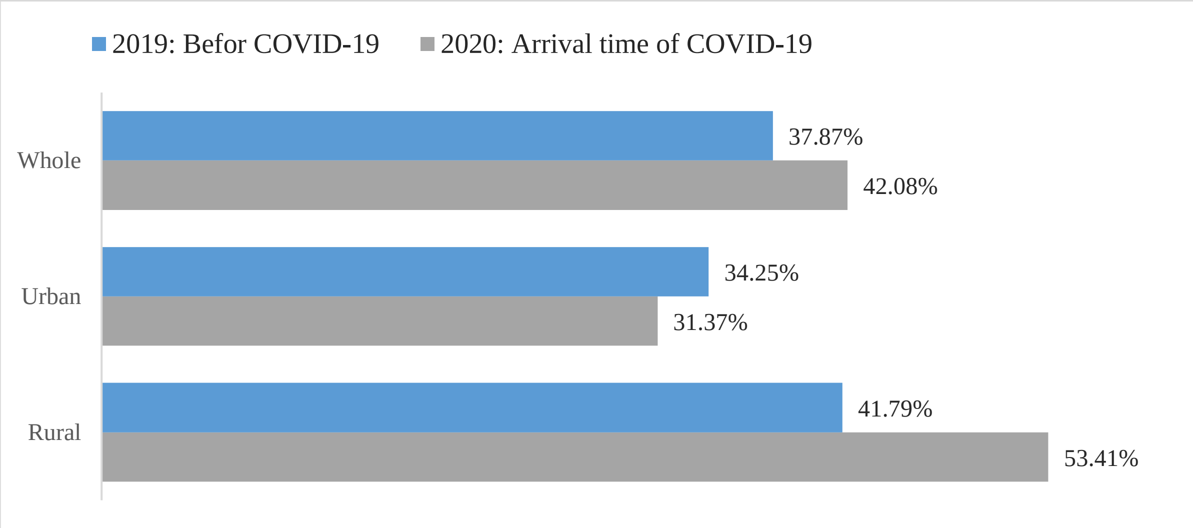

Figure 6- The ratio of food expenditure in Iran
Source: Author's own compilation

Table 6- Rural and Urban regions: pre-pandemic (2019)

	L. meat	P. meat	A. meat	Dairy	Eggs	A.Fats
Expenditure elasticity						
Rural	2.03	0.78	1.60	0.682	0.39	1.48
Urban	1.81	0.75	1.47	0.685	0.27	1.41
Hicksian (Compensated)						
Rural						
L. meat	-0.48	0.16	0.003	0.27	0.02	0.01
P. meat	0.08	-0.63	0.16	0.25	0.08	0.05
A. meat	0.015	1.15	-2.82	1.03	0.37	0.24
Dairy	0.17	0.30	0.17	-0.69	0.01	0.03
Eggs	0.04	0.27	0.17	0.04	-0.38	-0.14
A.Fats	0.15	0.75	0.52	0.38	-0.66	-1.15
Urban						
L. meat	-0.45	0.09	0.03	0.28	0.02	0.02
P. meat	0.07	-0.62	0.18	0.25	0.04	0.06
A. meat	0.12	0.91	-2.42	0.87	0.30	0.20
Dairy	0.21	0.25	0.18	-0.69	0.004	0.03
Eggs	0.06	0.17	0.21	0.1	-0.29	-0.18
A.Fats	0.20	0.66	0.47	0.37	-0.58	-1.12

Source: Author's own compilation

Table 7- Rural and Urban regions: during pandemic (2020)

	L. meat	P. meat	A. meat	Dairy	Eggs	A.Fats
Expenditure elasticity						
Rural	1.99	0.78	1.57	0.68	0.41	1.61
Urban	1.79	0.75	1.45	0.68	0.32	1.53
Hicksian (Compensated)						
			Rural			
L. meat	-0.62	0.22	0.07	0.28	0.02	0.007
P. meat	0.12	-0.50	0.07	0.19	0.06	0.04
A. meat	0.31	0.55	-2.74	1.08	0.39	0.39
Dairy	0.19	0.24	0.18	-0.70	0.03	0.04
Eggs	0.04	0.17	0.15	0.07	-0.37	-0.07
A.Fats	0.07	0.70	0.84	0.57	-0.41	-1.78
			Urban			
L. meat	-0.56	0.15	0.09	0.28	0.02	0.01
P. meat	0.12	-0.48	0.08	0.18	0.03	0.04
A. meat	0.38	0.41	-2.38	0.93	0.32	0.33
Dairy	0.24	0.19	0.19	-0.69	0.01	0.04
Eggs	0.05	0.11	0.17	0.04	-0.30	-0.09
A.Fats	0.17	0.57	0.75	0.54	-0.37	-1.67

Source: Author's own compilation

The Welfare Effects

Welfare effects analysis provides critical insights into how COVID-19 pandemic, influence household welfare and purchasing power. This section examines the welfare implications of price and income changes on rural and urban households, focusing on variations in consumption patterns across ASF groups. The assessment leverages economic models to estimate compensating variation, offering a comprehensive understanding of disparities in welfare losses between regions and ASF categories. The IHEIS contains the required data for equation (8). Table 8 shows per capita consumption values in kilograms per month ($\sum q_i/\sum n_h$) for the households, where q_i and n_h are the quantity consumed and the number of household members respectively.

Table 8- ASF Consumption, 2019-20 (kg per month)

ASF Group	Per capita consumption: Whole	Per capita consumption: Urban	Per capita consumption: Rural	World average* (Kg monthly)
8-1: pre-pandemic (2019)				
Livestock meat	0.493	0.433	0.558	2.9
Poultry meat	1.633	1.616	1.651	1.2
Aquatic meat	0.190	0.208	0.171	1.5
Dairy products	3.338	3.172	3.514	1.5
Eggs	0.522	0.528	0.516	2
Animal-derived Fats	0.055	0.061	0.048	1
8-2: during pandemic (2020)				
Livestock meat	0.530▲	0.506▲	0.554▼	
Poultry meat	1.539▼	1.559▼	1.518▼	
Aquatic meat	0.179▼	0.201▼	0.156▼	
Dairy products	2.976▼	2.882▼	3.074▼	
Eggs	0.519▼	0.531▲	0.506▼	
Animal-derived Fats	0.050▼	0.056▼	0.043▼	

* On average from official sources.

The direction of the change (▲▼): The green upward arrow indicates an increase and the red downward arrow indicates a decrease.

Source: Authors

The per capita consumption of most ASF groups declined in 2020 compared to 2019, with the exception of livestock meat and eggs. Urban households notably increased their livestock meat consumption (from 433g to 506g) and slightly raised egg intake (from 528g to 531g). Conversely, dairy products experienced the sharpest decline, with rural consumption dropping from 3.1 to 2.8 kg per person monthly and urban from 3.5 to 3 kg. This reduction highlights shifting dietary patterns, potentially driven by economic constraints or supply chain disruptions during the pandemic. Across the sample, ASF consumption predominantly decreased, except for livestock meat, reflecting uneven impacts on household nutrition and food priorities.

Table 9- CV due to change in ASF group prices, 2019-20

ASF Group	Whole	Urban	Rural
Livestock meat	9.4%	8.6%	10.2%
Poultry meat	13.8%	13.5%	14.2%
Aquatic meat	5.6%	6.6%	4.6%
Dairy products	24.2%	23.7%	24.7%
Eggs	4.7%	4.5%	4.9%
Animal-derived Fats	2.0%	2.2%	1.8%

Source: Author's own compilation

Table 9 highlights welfare losses due to price changes in ASF groups, with losses ranging from 1.8% (fats group in rural areas) to 24.7% (dairy products in rural areas). Rural households generally experienced higher welfare losses, reflecting their greater vulnerability to price fluctuations. However, urban regions incurred greater losses in specific groups such as livestock, aquatic, and fats, potentially due to differing consumption patterns or income constraints. The average welfare loss across all groups was 9.9%, with a standard deviation of 8% and a range of 23%, indicating significant variability in impacts. These disparities underscore the unequal burden of economic shocks on rural and urban populations, emphasizing the need for targeted policies to mitigate adverse welfare effects, particularly in vulnerable rural communities.

Conclusion

This study examined the economic impacts of the COVID-19 pandemic on Iranian households, with a specific focus on ASF. ASFs were prioritized due to their critical role in providing high-quality protein and essential micronutrients, including iron, zinc, and vitamin B12, that are vital for maintaining health during crises. Unlike plant-based proteins, ASFs offer complete amino acid profiles and higher nutrient bioavailability. However, their higher cost and sensitivity to supply chain disruptions make them particularly vulnerable during economic shocks, thereby posing heightened food security risks. The decision to focus on ASFs reflects both their nutritional significance and their disproportionate burden on household budgets, particularly in MI countries.

The pandemic-induced economic shock led to negative GDP per capita growth across all income groups in 2020, reversing a previously upward trend. Against this backdrop, the study investigated how income and price shocks influenced household consumption patterns, food expenditure allocation, and welfare losses. Using cross-sectional data from 2019 and 2020 and applying QUAIDS model, the analysis covered six ASF groups: livestock meat, poultry meat, aquatic meat, dairy products, eggs, and animal fats.

The results reveal substantial disparities between rural and urban households in terms of expenditure behavior and vulnerability. Eggs, poultry meat, and dairy products were identified as necessary goods, with relatively low expenditure elasticities of 0.33, 0.77, and 0.68, respectively. In contrast, livestock meat, aquatic meat, and animal fats displayed higher elasticities, classifying them as luxury goods more sensitive to income changes. Welfare losses were most pronounced for dairy products, with an overall decline of 24.2%, rising to 24.7% among rural households. Poultry meat also saw significant welfare losses, particularly in rural areas, where losses reached 13.8%. Notably, price elasticities were more pronounced than expenditure elasticities, suggesting that households were more responsive to price fluctuations than income changes. This trend was especially evident among rural households, which displayed higher price sensitivity despite facing relatively smaller price increases, highlighting their limited budgetary resilience.

These findings underscore the fragility of food security during systemic shocks, especially for rural populations that depend heavily on ASFs for protein intake. The Iranian case aligns with similar patterns observed in other MI economies. For example, Tian *et al*. (2022) found that rural households in China faced greater vulnerability to ASF price volatility during the pandemic, mirroring trends observed in Iran. Likewise, Adelaja *et al*. (2021) reported that rural communities in Sub-Saharan Africa allocated a growing share of their budgets to food in response to crises, a finding consistent with the increase in rural Iranian food expenditure from 47% to 53%. The classification of ASFs into necessary and luxury goods also resonates with prior literature, including Alston *et al*. (1995), who found that staple items like eggs and dairy generally exhibit lower income elasticities than higher-value proteins such as livestock meat.

In conclusion, the study contributes to a broader understanding of the nutritional and economic vulnerabilities exposed by the COVID-19 pandemic. By highlighting the differentiated impacts across ASF categories and between urban and rural populations, the findings offer valuable insights for policymakers seeking to design targeted interventions to safeguard food security during future crises. Efforts to stabilize prices, support household incomes, and ensure access to essential nutrients will be critical in enhancing resilience among the most vulnerable groups.

Policy Implications

The findings of this study offer valuable insights for the development of targeted policy measures aimed at enhancing food security and economic resilience in the post-COVID-19 period. Although the acute phase of the pandemic has passed, households continue to face long-term challenges such as income instability and rising food prices. By analyzing food demand for 39,000 Iranian households during the pandemic, this study contributes critical evidence for shaping effective strategies to mitigate the impacts of similar future crises, especially across urban and rural settings.

ASFs remain a central component of Iranian diets, maintaining a substantial share of household food expenditure despite significant price increases. The focus on ASFs, rather than plant-based foods, reflects both their nutritional importance and their heightened sensitivity to income and price fluctuations, making them a crucial marker of household food security. The observed rise in ASF expenditures in 2020 was influenced by supply chain disruptions, inflation, and reduced purchasing power stemming from economic contraction. Rural households, in particular, exhibited greater price sensitivity due to limited income diversification and heavier reliance on local markets.

To address these vulnerabilities, policymakers must prioritize the resilience of ASF supply chains. Key actions include investments in infrastructure, improved storage and distribution systems, and financial support mechanisms for producers to buffer against future economic shocks. Promoting local production and diversifying supply sources can reduce import dependency and help stabilize domestic prices. Strengthening regulatory oversight and fostering public-private partnerships will also be essential to ensure more efficient supply chain management during periods of disruption.

Given the divergent needs of urban and rural populations, a differentiated policy approach is warranted. For urban households, who experienced a decline in the share of food expenditure-price-based interventions such as subsidies or price controls on essential ASFs could alleviate the financial burden. In contrast, rural households where food expenditure shares rose significantly would benefit more from expanded social services, including access to healthcare, education, and targeted financial aid. This recommendation is consistent with

Engel's Law, which suggests that rural households allocate a larger portion of their income to food, underscoring the importance of non-food support mechanisms to enhance overall welfare.

To support urban households more effectively, policies should aim to stabilize food prices, increase access to affordable ASFs, and extend income support to low-income populations. Government-led price stabilization programs could reduce volatility and enhance affordability. For rural populations, interventions should focus on infrastructure development, capacity-building initiatives for small-scale farmers, and targeted subsidies to lower both production and consumption costs. Expanding social safety nets and fostering community-based agricultural initiatives can empower rural households to meet their nutritional needs more sustainably.

Although the focus of this study is on ASFs, it also highlights the long-term importance of promoting dietary diversification through plant-based protein alternatives. Compared to ASFs, plant-based proteins are typically more affordable, environmentally sustainable, and less susceptible to supply chain disruptions. Exploring substitution strategies especially in culturally receptive regions, can help bolster resilience and align with broader global movements toward sustainable diets. Future research in this area can inform policies that encourage gradual shifts toward more diverse and resilient dietary patterns.

In sum, this study calls for a comprehensive, multi-faceted policy response to food insecurity—one that accounts for the distinct needs of both urban and rural households. Strengthening ASF supply chains, tailoring support policies, and promoting sustainable dietary diversification are all essential steps toward improving household welfare and economic stability in the post-pandemic era. These recommendations are aligned with existing literature, such as Barrett *et al.* (2020), who emphasize the need for targeted rural interventions, and Willett *et al*. (2019), who advocate for dietary shifts to enhance sustainability and resilience. Collectively, these insights reinforce the relevance and applicability of the current study's policy guidance.

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مقاله پژوهشی

جلد ۳۹، شماره ۲، تابستان ۱۴۰۴، ص. ۱۳۸-۱۱۷

نابرابری‌های روستایی-شهری در تقاضای غذای حیوانی و زیان‌های رفاهی در ایران طی کووید-۱۹: رویکرد QUAIDS

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تاریخ دریافت: ۱۴۰۳/۰۳/۷
تاریخ پذیرش: ۱۴۰۴/۰۲/۲

چکیده

پاندمی کووید-۱۹، چالش‌های جهانی عمده‌ای ایجاد کرد، از جمله نرخ رشد منفی درآمد سرانه در تمامی گروه‌های درآمدی کشورها در سال ۲۰۲۰. زنجیره تأمین پروتئین، به‌ویژه با منشأ حیوانی (ASF)، با فشارهای فزاینده‌ای از هر دو سوی عرضه و تقاضا مواجه شد که منجر به نوسانات قیمتی گردید. این مطالعه، تأثیر شوک درآمدی بر الگوهای مخارج غذایی و رفتار مصرفی را با تمرکز بر این نوع غذاها بررسی می‌کند. داده‌های بودجه خانوارهای ایرانی برای سال‌های ۲۰۱۹ (پیش از پاندمی) و ۲۰۲۰ (طی پاندمی) با بکارگیری مدل سیستم تقاضای تقریباً ایده‌آل درجه دوم (QUAIDS) تحلیل شد. یافته‌ها سه بینش کلیدی ارائه دادند: ۱) سهم متوسط مخارج غذایی از ۳۷٪ به ۴۲٪ افزایش یافته است، ضمن رشد شدیدتر در مناطق روستایی؛ ۲) کشش‌های مخارج برای هر شش گروه ASF شامل گوشت دام، آبزیان، طیور، محصولات لبنی، تخم‌مرغ و چربی‌ها، مثبت مشاهده شد در حالی‌که کشش‌های خودقیمتی به‌طور نسبی کوچکتر بودند؛ و ۳) زیان‌های رفاهی در این شش گروه، از ۲٪ تا ۲۴٪ متغیر بود، که ناشی از عدم تعادل سیاستی و اختلالات زنجیره تأمین بود. خانوارهای روستایی به جز در گروه چربی‌ها، زیان‌های رفاهی بیشتری متحمل شدند. این مطالعه مداخلات هدفمند به شکل سیاست های حمایتی قیمتی برای مناطق شهری و حمایت اجتماعی برای مناطق روستایی، پیشنهاد می‌کند. برای تقویت واکنش‌های سیاستی و بهبود امنیت غذایی بلندمدت، تحقیقات آتی می‌تواند پتانسیل جایگزینی پروتئین‌های گیاهی را به‌عنوان گزینه‌های پایدار و مقرون‌به‌صرفه ارزیابی کند. این یافته‌ها راهنمایی ارزشمندی برای سیاست‌گذاران در راستای بهبود تاب‌آوری و ثبات اقتصادی در دوران پساپاندمی ارائه می‌دهند.

واژه‌های کلیدی: زیان رفاهی، کووید-۱۹، غذاهای با منبع حیوانی (ASF)، مدل QUAIDS، ایران

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https://doi.org/10.22067/jead.2025.88095.1267

Journal of Agricultural Economics & Development

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

Research Article
Vol. 39, No. 2, Summer 2025, p. 139-149

Impact of Agricultural Policies on Smallholders' Food insecurity Resilience in Iran: Evidence from Iran

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Received: 26-12-2024 Revised: 07-03-2025 Accepted: 17-03-2025 Available Online: 17-03-2025	**How to cite this article:** Zarif Moradin, Sh., Daneshvar Kakhki, M., & Sabouhi Sabouni, M. (2025). Impact of agricultural policies on Smallholders' food insecurity resilience in Iran: Evidence from Iran. *Journal of Agricultural Economics & Development, 39*(2), 139-149. https://doi.org/10.22067/jead.2025.91359.1322

Abstract

One of the essential goals of societies, primarily developing and underdeveloped countries, is to eradicate poverty and achieve sustainable development. As vulnerable individuals in many communities' face growing economic, environmental, and political challenges, proactive crisis management by governments and policymakers—aimed at increasing the productivity of key economic sectors such as agriculture—has become essential. The efficiency of the farm sector is not only crucial for ensuring national food security, but it also significantly impacts the livelihoods, incomes, and resilience of rural smallholders. The purpose of this study is to investigate the impact of agricultural support policies on the resilience of rural farmers in the Fariman region. The study area is the Hossein Abad Rekhneh Gol village, Iran, and the data were collected through documentation and the use of questionnaires. The Resilience Index Measurement and Analysis (RIMA) introduced by the FAO has been used to determine the resilience of rural farmers. Additionally, the distribution of subsidized fertilizers to farmers as a common agricultural support policy in the country has been chosen. The impact of this agricultural support policy on the resilience of rural farmers has been estimated using the propensity score matching method in this study. The study results indicate that households eligible to receive subsidized fertilizers have higher resilience on average compared to households that are not eligible. Based on the research findings for the study area, it is recommended that rural smallholders be prioritized in the allocation of subsidized fertilizers, which is constrained by quantity and budget limitations imposed by the government, compared to large-scale farmers. Additionally, facilitating rural farmers' access to the available agricultural wells owned by non-private institutions can potentially improve farmers' resiliency.

Keywords: Agricultural support policies, Food insecurity, Propensity score matching, Resilience, Rural farmers

Introduction

The concept of resilience is considered as the capacity of a system, family, or individual to withstand various shocks and risks, which has been on the agenda of all countries as a new concept of development in the 2030 Sustainable Development Agenda (d'Errico *et al.*, 2021; FAO, 2018). Achieving food security and combating poverty and hunger have become central to the agricultural policies of various countries, especially in developing and underdeveloped societies. Two major global paradigms, i.e., the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs), prioritized the

https://doi.org/10.22067/jead.2025.91359.1322

eradication or reduction of global poverty and hunger. Accordingly, medium-term and short-term agendas have been outlined in different communities to achieve these overarching goals (United Nations 2015a, 2015b).

The agricultural sector plays a crucial and strategic role in ensuring food security and significantly contributes to broader economic development. In both underdeveloped and developing countries, agriculture drives growth by producing and supplying food, generating employment through the expansion of upstream and downstream industries, and increasing foreign exchange earnings via the growth of non-oil exports. Therefore, the development of the agricultural sector is considered one of the most effective tools for reducing poverty in communities. (Alam *et al*., 2023). Iran, as a developing country, is no exception to this trend and requires the development of its agricultural sector to stimulate sustainable and inclusive economic growth. Increasing the productivity of the agricultural sector, in addition to ensuring the country's food security, can significantly improve the livelihoods and employment status of Iran's rural population. The small-scale, peasant production system is the most prevalent mode of production, accounting for more than 85% of agricultural production units in the country.

In rural areas and among farmer households, food security and resilience are deeply intertwined. Food security not only ensures that families have consistent access to sufficient, safe, and nutritious food, but it also strengthens their resilience to economic and environmental shocks (Zarif Moradian *et al*., 2022). Resilient households are better able to adapt to challenges such as fluctuating market prices, natural disasters, and climate change, which are common in agricultural-dependent regions. Improving food security in these areas, through both enhanced agricultural productivity and sustainable farming practices, enables farmers to buffer against shocks, maintain stable incomes, and ensure the well-being of their families. As a result, strengthening food security directly contributes to the overall resilience of rural communities, fostering long-term stability and growth.

In general, supportive policies in Iran's agricultural sector can be introduced through three general frameworks. The first group includes tax exemptions, legal privileges, tariff barriers, and preferential rates for bank credits. The second group includes explicit and implicit subsidies for the production and consumption of agricultural commodities, including input subsidies and price support measures. Finally, the third group can be introduced as public services and infrastructure in the agricultural sector, which includes budget payments for the development of agricultural infrastructure, research and extension, and other civil activities in the agricultural sector (Mojtahed & Esfahani, 1989).

Granting production subsidies and setting guaranteed prices for strategic agricultural products are among the most common types of direct support for agricultural producers in Iran. The objective of the government and policymakers in adopting and implementing the policies mentioned above is not only to enhance the productivity of the farm sector but also to increase the income of farmers and improve their livelihood status, especially rural smallholders. Regarding the improvement of the livelihood status of rural smallholders, one can refer to ensuring their food security and income stability, as agricultural producers are constantly faced with technical, economic, and environmental challenges due to the nature of farming production. Therefore, identifying and implementing measures that will increase the resilience of rural smallholders is of great importance. Given that a significant percentage of agricultural producers in Iran are made up of rural smallholders and the importance of their resilience to food insecurity, considering measures and policies that lead to an increase in the resilience of rural farmers against various shocks is essential. Upon reviewing the existing literature, a significant gap becomes apparent. While many studies have focused on the impact of agricultural support policies on food insecurity, few have explored their effects on farmers' resilience to food insecurity. Table 1 shows the aforementioned studies.

Table 1- Summarized literature

Number	Surveyed study	Location	Policy measures / Programs (in Agriculture)	Affected factors
1	(Hunt *et al.*, 2011)	Australian villages	Agricultural extension; extension program in the Tasmanian sheep industry as a supporting case study	Improving the capacity-building and resilience in rural industries and communities
2	(Schouten *et al.*, 2012)	Netherlands	Rural development policies; Impact of Modulation from a Resilience Perspective	Increasing an average score of 79/156 on the criteria for developing resilience.
3	(Ambelu *et al.*, 2017)	Southern Ethiopia	The intervention measures on the livestock and infrastructure of resilience dimensions	Improving the resilience of rural communities.
4	(d'Errico *et al.*, 2020)	Lesotho	Cash transfer projects; Child Grant Program.	Positive and significant short-term impact on less resilient households.
5	(Buitenhuis *et al.*, 2020)	Netherlands	Common agricultural policies (CAP)	Strongly support the robustness of the resilience of farming system.
6	(Anantha *et al.*, 2021)	South Asia	Management practices on sustainable crop production	Improving climate resilience in smallholder farming systems
7	(Maia *et al.*, 2021)	Brazil	Climate resilience program; a set of climate-smart production practices and locally-adapted technologies.	Improving the production practices, land management, and the quality of life of the farmers.
8	(Baffour-Ata *et al.*, 2023)	Ghana, Bono east Region,	Climate smart agriculture (CSA) program.	Positive and significant effect on the resilience of smallholder farmers.
9	(Ali *et al.*, 2023)	Ethiopia	Climate smart agriculture (CSA) program.	Increasing smallholder farmers' resilience
10	(Temesgen Gelata *et al.*, 2024)	Ethiopia	Dairy contract farming adoption	Increasing households' resilience to food insecurity by 18%

This research intends to examine the effect of a common supportive policy in the Iranian agricultural sector on the resilience of rural smallholders against food insecurity. This study aims to examine the effect of a specific agricultural support policy-subsidized fertilizer distribution-on the resilience of rural smallholder farmers. It is believed that the proper implementation and adoption of each type of support policy in this sector not only provides the means to achieve the overarching goals, such as achieving sustainable food security, but also leads to an improvement in the livelihood status and resilience of farmers.

Materials and Methods

Study Area and Data

Fariman County, Iran, with an area of 3,356 square kilometers, is located the capital of Khorasan Razavi Province. The county has two districts, four cities, five townships, and 148 inhabited villages. The total population of Fariman County is 99,001, of which 85,966 live in cities and 40,035 (44.40%) live in villages (Iran Statistics Center, 2015). Fariman County is considered an important agricultural production hub in Khorasan-Razavi province due to its extensive irrigated and rainfed farmlands and high capacity for agricultural, horticultural, and livestock production. Considering the significance of agricultural production in Fariman County, examining the resilience capacity of farmers in this region and the impact of agricultural support policies on their resilience are of undeniable importance.

With the objective of studying the impact of agricultural support policies on the resilience of rural farmers, the following criteria have been considered for selecting the target village in Qalandarabad district: (i) The study village should have a sufficient number of farm households for whom agriculture is the main source of income for the household head; (ii)

The agriculture of the households under study should include both rain-fed and irrigated farming; and (iii) The farmers should reside in the same village.

According to the opinions of experts from the Agriculture organization and the Agricultural Support Services Organization, the village of Hosein Abad Rekhneh Gol has been selected for the study due to the impressive number of rural employment in the agricultural sector and the availability of diverse water resources in kinds of wells and qanats. The geographical coordinates of Hoseynabad-e Rekhneh Gol are approximately: Latitude: 35°32′38″ N and Longitude: 60°04′55″ E.

Data Collection and Parametrization

The resilience of the statistical population in facing food insecurity was estimated using the results of a previous study (Moradian *et al*., 2023) conducted in Hossein Abad Rekhneh Gol village. The households of rural farmers who were part of the study (Moradian *et al*., 2023) were surveyed about their receipt of agricultural support subsidies. The impact of farming subsidies on the resilience index against food insecurity was then calculated using the methods detailed in section 3 of this article. The statistical sample group comprised 149 farm households, selected through a random sampling method from a total of 214 farmers in the village.

Farmers who received subsidized fertilizers during the agricultural year are considered the treatment group, and farmers who did not receive subsidized fertilizers are in the control group. Table 2 shows the number and share of the treatment and control groups.

Table 2- The number and share of rural households in the treatment and control groups

Control group (Farmers who did not receive subsidized fertilizer)	Treatment group (Farmers who received subsidized fertilizer)	Description
76	73	Number (household)
51%	49%	Share of total (percentage)

Source: Research findings

Methods

The methodology employed in this research comprises two main parts. The first part estimates the resilience index of rural smallholders against food insecurity, and the second part examines the effect of the implemented support policies on this index.

Estimating the Resilience Index of Rural Smallholders against Food Insecurity: In this study, the resilience index of rural smallholders was estimated using the RIMA (Resilience Index Measurement Analysis), which was introduced by the FAO in 2008 and expanded in 2016. The RIMA resilience index consists of four pillars, namely access to public services, assets, social safety nets, and adaptive capacity. Each of these pillars is composed of a number of unobservable variables. To examine the resilience index (RIMA) against food insecurity, various food insecurity indicators can be utilized, including the Food Consumption Scale (FCI) and the Household Hunger Scale (HHS). Finally, after separately calculating the resilience index's pillars and the food insecurity indicators, the RIMA Resilience Index is obtained using methods such as structural equation models (MIMIC[1]). The RIMA resilience index can range from zero to one hundred, with lower values meaning less resilience to food insecurity and vice versa.

Estimating the Impact of Agricultural Support Policies on the Resilience of Rural Farmers: In general, the policies of purchasing agricultural products at guaranteed prices and providing subsidies for agrarian inputs are considered the most significant agricultural support policies implemented in various

1- Multiple Indexes and Multiple Causes

regions, including the area under investigation in this study. The guaranteed price policy, primarily applicable to wheat, involves the government announcing the purchase rate for wheat for the upcoming agricultural year, allowing farmers to supply their produce to the government.

The policy of granting agricultural input subsidies, a recent initiative, is a comprehensive support system for farmers. It includes granting credit and financial facilities, distributing agrarian inputs, and other facilities. Notably, among these, the allocation of subsidized fertilizers plays a crucial role. These fertilizers, distributed based on farmers' share of agricultural water ownership, directly enhance their productivity and income. Other required inputs are obtained by farmers in the free market. Given that some farmers in the study, due to low quantity or quality of harvested wheat or other factors, choose not to participate in the wheat guaranteed price policy and instead sell their product on the open market and that yield differences further complicate the assessment of this policy's impact on farmer resilience, this study focuses on evaluating the impact of the subsidized fertilizer distribution policy on the resilience of rural farmers. As mentioned, the main objective of this study is to examine the effects of subsidized fertilizer distribution on the RIMA resilience index, which is called the Resilience Capacity Index (RCI) of rural households. In this regard, the Matching Method is considered an effective tool for evaluating the effect of a specific treatment (for example, an agricultural policy) on a group of people in society. In empirical research, matching is defined as pairing and comparing treatment group units with control group units based on observable characteristics (Independent variables). This method was first used by Rosenbaum and Rubin (Rosenbaum & Rubin, 1985) and has since been extensively used in the field of market policy evaluation (Filsaraee, 2015).

Estimation Procedure

To estimate the propensity score, the probability of treatment participation is first calculated for all observations using observed variables as predictors. Subsequently, individuals from the control group are matched to those in the treatment group based on these scores. Logit or Probit models are commonly employed to estimate the probability of participation. In this study, the treatment is the use of agricultural support policies (subsidies fertilizer), and the independent variables include the pillars of the resilience RIMA index such as access to public services (ABS), assets (AST), social safety nets (SSN), and adaptive capacity (AC). The experimental model is as follows:

$$Y = \alpha + ABS_i X_i + AST_i X_i + SSN_i X_i + AC_i X_i \qquad (1)$$

The Average Treatment Effect on the Treated (ATT) is considered the parameter of interest in the PSM analysis. In this study, ATT refers to the average effect of agricultural support policies (subsidies fertilizer) on the resilience of the rural households under study. ATT is calculated by using the matching of observations in the treatment group and the control group that are close in terms of propensity scores, as follows:

$$ATT\,(x) = E(Y_{1i}|T_i = 1) - E(Y_{0i}|T_i = 1) \qquad (2)$$

Descriptively, the PSM estimate is simply a difference in means between the treatment group and the control group, where the means are weighted averages using the weights of the distribution of propensity scores to participate (Pishbahar Esmaeel, 2017).

In the research literature, various methods of propensity score matching are used to match two treatment and control groups with similar propensity scores to calculate ATT. Given that the choice of matching estimator depends heavily on the characteristics of the data under consideration and the structure of the study, the Radius estimator is used in this study.

Results

Based on the mentioned results, out of the 149 households examined, 33 households (22%) are highly resilient, 82 households (55%) are resilient, 26 households (18%) are relatively resilient, and finally, eight households (5%) are vulnerable to food insecurity.

Table 3 shows the results of comparing the means of the two treatment and control groups for the independent variables of the model before matching.

Table 3- Comparison of the average resilience pillars in two control and treatment groups

Pvalue	T	Standard deviation		Mean		Independent variables
		Treatment group	Control group	Treatment group	Control group	
0.00	4.66	0.14	0.56	0.36	-0.35	Access to Basic Service (ABS)
0.00	-11.17	0.81	0.65	0.68	-0.66	Assets (AST)
0.38	0.86	1	1	0.17	0.17	Social Safety Nets (SSN)
0.00	-0.5	0.96	0.86	0.4	-0.39	Adaptive Capacity (AC)

Source: Research findings

As can be seen from the Table 3, before matching, the social safety net variable does not statistically differ between the control and treatment groups. However, there is a statistically significant difference between the control and treatment groups in terms of the variables of access to public services, assets, and adaptation capacity. These differences indicate that there is sample selection bias, and therefore, matching of households from the two groups is necessary before examining and evaluating the effect of the subsidized fertilizer distribution on household resilience capacity.

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Table 4- Propensity Score Matching calculations - The Probit model results

P-value	T	Coefficients	Variables
0.03	2.10	0.39	Access to Basic Service (ABS)
0.00	6.05	1.49	Assets (AST)
0.26	-1.11	-0.14	Social Safety Nets (SSN)
0.14	1.47	0.24	Adaptive Capacity (AC)
0.97	0.03	0.005	Intercept
Log likelihood: 50.42	LR Chi2: 105.66		Prob 0.00

Source: Research finding

Table 5 explains the estimated propensity score. Once the propensity score has been calculated for each observation, it is necessary to ensure that there is an overlap in the propensity score range between the control and treatment groups. This range is called the region of common support and is used to determine the optimal number of blocks.

Table 5- Descriptive statistics of the estimated Propensity Score Matching

Mean	Smallest	Percentiles	Thresholds
0.686	0.134	0.137	1%
	0.137	0.167	5%
Std. Dev	0.145	0.197	10%
0.289	0.145	0.473	25%
	(Largest)	0.758	50%
Variance.	0.999	0.932	75%
0.082	0.999	0.990	90%
	0.999	0.999	95%
Observations 103	1	0.999	99%

Source: Research findings

Based on Table 5, the region of common support ranges from 0.134 to 1. The optimal number of blocks was determined to be five, ensuring that within each block, the average propensity score is statistically similar between the treatment and control groups. This stratification helps satisfy the balancing property required for unbiased treatment effect estimation.

Table 6 shows the results of the test of the propensity score's balancing property. Based on Table 6, which indicates the number of treatments and controls in each block, the balance of the blocks has been achieved.

Table 6- The balance test of the estimated propensity score

Sum	**Receiving and not receiving subsidized fertilizer**		**Propensity score blocks**
	1	**0**	
12	3	9	0.134
9	5	4	0.2
12	5	7	0.4
23	16	7	0.6
47	44	3	0.8
103	73	30	Sum

Source: Research findings

Table 7 shows the effect of the subsidized fertilizer distribution support policy on the resilience index of rural farmers in Hossein Abad Rekhneh Gol village. Table 7 shows the results of using the propensity scores obtained from the probit model and matching the propensity scores using the radius method. The radius method was chosen from among the other available algorithms for calculating the ATT (Average Treatment Effect on the Treated).

Table 7- The effect of the support policy of subsidized fertilizer distribution on the RCI of rural farmers

Standard Deviation	**t**	**Numbers of Control Group**	**Numbers of Treatment**	**Average Treatment effect on the Treated**	**Treatment**	**Dependent Variable**
1.55	4.08	73	30	6.33	Receiving subsidized fertilizer	Resilience Capacity Index

Source: Research findings

The t-statistic between the control and treatment groups is significant (Table 7) meaningthat the distribution of subsidized fertilizers, as an agricultural support policy, has a significant effect on the resilience index of rural farmers in Hossein Abad Rakhneh Gol village. The mean resilience of the treatment group (the group that received subsidized fertilizers) is higher in the face of food insecurity than the control group (the group that did not receive subsidized fertilizers).

Conclusion and Discussion

In general, unpredictable crises in the political, economic, and environmental fields are considered to be significant factors in food insecurity in developing countries. Iran, as a developing country, has always been and continues to face various shocks, such as climate change, drought, and political and economic sanctions. These challenges and problems have had a significant impact on different economic sectors, especially agriculture and industry, in recent years.

Since resilience is considered the capacity for absorption, adaptation, and transition of an individual or household in the face of shock (Béné *et al*., 2012), increasing resilience requires long-term measures that cannot be achieved without the support of policymakers. These measures include a wide range of actions, including the creation and improvement of infrastructure and agriculture, especially in rural areas. Accordingly, the objective of this study is to assess how the subsidized fertilizer distribution support policy influences the resilience of rural farmers in Hossein Abad Rakhneh Gol village. In this regard, the propensity score matching approach has been used. Based on the results obtained from the mentioned method, it was found that the average resilience of households that received subsidized fertilizers is higher than the group of households that did not benefit from this policy.

Based on the results of the study of (Moradian *et al.*, 2023), among the variables that create the asset pillar in the resilience index, the wheat yield variable plays a significant role. Therefore, factors that lead to an increase in the yield of agricultural products can also increase their resilience in the face of food insecurity. One of the factors that have a significant impact on improving the yield of agricultural products, including wheat, is the use of chemical fertilizers, including nitrogen, phosphorus, and potassium. In the cultivation year 2022-2023, in which the data was collected, these fertilizers were the only subsidized input distributed by the government to farmers. Due to the difference between subsidized and market prices, majority of the farmers who were unable to receive this subsidy due to lack of agricultural water were unable to buy it in the market in cash, too. This can have a significant impact on reducing the yield of their products and consequently affect their resilience.

Creating an understanding and awareness of rural farmers' resilience and identifying the factors and policies that affect their resilience will lead to directing the policy path in the form of improving the weaknesses of different regions and will result in significant savings in budget and time. These two factors are among the important and limiting factors in various policy-making.

Finally, based on the study results, it is recommended that:

- The number of available agricultural rental wells for rural farmers should be increased. Additionally, extending the contract duration with rural farmers could lead to an increase in the productivity of agricultural production in rural areas.
- Necessary changes in the resolution related to fertilizer distribution laws should be made in a way that small rural landowners (including rain-fed farmers and irrigated farmers) receive subsidized fertilizers based on the area under cultivation in each agricultural year. In the allocation of subsidized fertilizers, which are limited by quantity and budget constraints from the government, rural farmers should be prioritized over large landowners.

Limitations

Policies supporting agricultural producers in Iran mainly involve providing subsidies for production inputs and purchasing essential products, particularly wheat, at guaranteed prices by the government. Considering the approach taken in this study regarding the impact of agricultural support policies on the resilience of rural farmers, it may not be possible to assess the effectiveness of the policy of purchasing agricultural products at guaranteed prices in improving the livelihoods and resilience of rural farmers due to differences in eligible conditions.

Since no study has been done on the impact of the policy of purchasing agricultural products at guaranteed prices on the resilience of farmers in Iran, this could be an area of interest for researchers in the future.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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مقاله پژوهشی

جلد ۳۹، شماره ۲، تابستان ۱۴۰۴، ص. ۱۴۹-۱۳۹

تأثیر سیاست‌های کشاورزی بر تاب‌آوری کشاورزان خرده مالک در برابر ناامنی غذایی در ایران

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تاریخ دریافت: ۱۴۰۳/۱۰/۰۶
تاریخ پذیرش: ۱۴۰۳/۱۱/۲۷

چکیده

یکی از اهداف اساسی جوامع، به‌ویژه در کشورهای در حال توسعه و کمتر توسعه‌یافته، ریشه‌کن کردن فقر و دستیابی به توسعه پایدار است. با توجه به اینکه افراد آسیب‌پذیر در بسیاری از جوامع با چالش‌های اقتصادی، زیست‌محیطی و سیاسی روزافزون مواجه هستند، مدیریت پیشگیرانه بحران‌ها توسط دولت‌ها و سیاست‌گذاران، به‌ویژه در راستای افزایش بهره‌وری بخش‌های کلیدی اقتصادی مانند کشاورزی، به امری ضروری تبدیل شده است. کارآیی بخش کشاورزی نه تنها برای تضمین امنیت غذایی ملی از اهمیت بالایی برخوردار است، بلکه تأثیر عمده‌ای بر معیشت، درآمدها و تاب‌آوری کشاورزان روستایی کوچک دارد. هدف این مطالعه، بررسی تأثیر سیاست‌های حمایتی کشاورزی بر تاب‌آوری کشاورزان روستایی در منطقه فریمان است. این مطالعه بر روستای حسین‌آباد رخنه‌گل در ایران متمرکز بوده و داده‌ها از طریق مصاحبه و با استفاده از پرسشنامه‌ها جمع‌آوری شده است. برای اندازه‌گیری میزان تاب‌آوری کشاورزان روستایی از شاخص اندازه‌گیری و تحلیل تاب‌آوری (RIMA) که توسط سازمان خواربار و کشاورزی ملل متحد (FAO) معرفی شده است، استفاده گردیده است. همچنین، توزیع کودهای یارانه‌ای به کشاورزان، به‌عنوان یک سیاست حمایتی رایج کشاورزی در کشور، به‌عنوان متغیر مورد بررسی انتخاب شده است. تأثیر این سیاست حمایتی بر تاب‌آوری کشاورزان روستایی از طریق روش همسان‌سازی امتیاز تمایل (Propensity Score Matching) برآورد شده است. نتایج مطالعه نشان می‌دهد که خانوارهای واجد شرایط برای دریافت کود یارانه‌ای، به‌طور متوسط تاب‌آوری بالاتری نسبت به خانوارهایی که واجد شرایط دریافت این کود نبوده‌اند، دارند. بر اساس نتایج این تحقیق در منطقه مورد مطالعه، پیشنهاد می‌شود که کشاورزان روستایی کوچک در تخصیص کود یارانه‌ای، که با محدودیت‌های مقداری و بودجه‌ای دولت مواجه است، نسبت به کشاورزان بزرگ‌مقیاس در اولویت قرار گیرند. علاوه بر این، تسهیل دسترسی کشاورزان روستایی به چاه‌های کشاورزی موجود که تحت مالکیت مؤسسات غیرخصوصی هستند، می‌تواند به‌طور بالقوه تاب‌آوری کشاورزان را افزایش دهد.

واژه‌های کلیدی: تاب‌آوری، روش جورسازی، سیاست‌های حمایتی کشاورزی، کشاورزان روستایی، ناامنی غذایی

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https://doi.org/10.22067/jead.2025.91359.1322

Journal of Agricultural Economics & Development

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

Research Article

Vol. 39, No. 2, Summer 2025, p. 151-164

Digital Agricultural Marketing: Determinants of Consumer Engagement Intentions in Urmia, Iran

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Received: 09-01-2025 Revised: 08-02-2025 Accepted: 22-02-2025 Available Online: 22-02-2025	**How to cite this article:** Molaei, M., Rashidghalam, M., & Hosseinpour, B. (2025). Digital agricultural marketing: Determinants of consumer engagement intentions in Urmia, Iran. *Journal of Agricultural Economics & Development*, *39*(2), 151-164. https://doi.org/10.22067/jead.2025.91586.1325

Abstract

The importance of understanding consumer engagement with digital marketing in agriculture is highlighted by the rapid evolution of digital platforms, which are transforming traditional marketing approaches. This study investigates the factors influencing consumer intentions to engage with digital marketing of agricultural products in Urmia, Iran. Data were collected from 385 respondents through a structured questionnaire and analyzed using a logistic regression model. Results indicate that perceived usefulness, perceived ease of use, trust, information quality, and social influence positively and significantly impact engagement intentions. Demographic factors such as age (negatively), education level, and income (both positively) also play significant roles. Notably, prior online purchase experience emerged as a strong predictor of engagement intention, while price sensitivity showed a marginally significant negative effect. The study contributes to the literature by providing empirical evidence from a developing country context and offering a comprehensive model for understanding consumer behavior in digital agricultural marketing. Implications for marketers include developing user-friendly platforms, prioritizing trust-building mechanisms, and tailoring strategies to different demographic segments.

Keywords: Agricultural products, Consumer intentions, Digital marketing, Urmia

Introduction

Digital marketing in agriculture encompasses online and technology-driven promotional activities, such as social media, content marketing, and e-commerce (Tiago & Veríssimo, 2014; Michaelidou *et al*., 2011; Yadav & Rahman, 2017). These strategies aim to increase brand awareness, enhance customer engagement, and drive sales of agricultural products (Kutter *et al*., 2011). The adoption of digital marketing is driven by consumers' growing reliance on digital channels (Dlodlo & Dhurup, 2013). Successful implementation requires an understanding of the unique characteristics and challenges of the agricultural sector, including perishability, seasonality, and producer diversity (King *et al*.,

https://doi.org/10.22067/jead.2025.91586.1325

2010).

Digital marketing in agriculture has evolved significantly over the past decade, driven by advancements in technology and the increasing internet accessibility in rural areas. The integration of digital tools has enabled farmers to access real-time market information, weather forecasts, and best practices, thereby enhancing productivity and profitability (Deepa & Deborah, 2024). Social media platforms such as Facebook and Instagram, along with mobile applications have become pivotal in connecting farmers with consumers. These platforms facilitate direct sales, reducing the dependency on intermediaries and improving margins for farmers (Karle & Mishra, 2022). Additionally, digital marketing strategies have been instrumental in promoting sustainable agricultural practices and educating farmers about innovative techniques (Ijomah *et al*., 2024). The adoption of digital marketing in agriculture is not only transforming traditional farming practices but also contributing to the overall development of rural economies (Deepa & Deborah, 2024).

Understanding consumer intentions towards digital marketing is crucial in today's rapidly evolving digital landscape (Patel & Chauhan, 2022). As businesses increasingly rely on digital channels to reach and engage their target audience, comprehending the underlying motivations and attitudes of consumers becomes essential for effective strategic development (Haris, 2024). Research indicates that consumer intentions in the digital realm are influenced by a complex interplay of factors, including trust, perceived usefulness, and personal relevance (Cho & Sagynov, 2015). By gaining insights into these intentions, marketers can tailor their approaches to align with consumer expectations, potentially leading to improved engagement rates and higher conversion metrics (Erislan, 2024). Furthermore, a deeper understanding of consumer intentions enables organizations to anticipate shifts in digital behavior, allowing for more agile and responsive marketing strategies in an increasingly competitive online environment (Sunarya *et al*., 2024).

Despite the growing importance of digital marketing in the agricultural sector, there is limited research on consumers' intentions and attitudes towards these marketing efforts for agricultural products, particularly in the context of Iranian cities. The factors influencing consumer acceptance and engagement with digital marketing of agricultural products remain poorly understood (King *et al*., 2010). Urmia, the largest city in West Azerbaijan Province, is renowned for its production of apples, grapes, and other agricultural products. Urmia serves as a significant urban market for agricultural goods in northwestern Iran. The city's strategic position near the borders of Turkey and Iraq further enhances its potential as a hub for agricultural trade in the region. Therefore, this study centers on Urmia, which is located in a fertile agricultural region, with an estimated population of approximately 790,000[1] in 2023. This knowledge gap hinders the development of effective digital marketing strategies tailored to the unique characteristics of agricultural products and their consumers in Urmia.

This study aims to investigate the key factors that influence consumer intentions to engage with digital marketing of agricultural products in Urmia, Iran. Drawing on constructs such as perceived usefulness, trust, and social influence, the research seeks to provide a comprehensive understanding of consumer behavior in this emerging marketing context.

Literature Review

Existing research highlights both the potential benefits and barriers, such as infrastructure constraints and data privacy concerns. Consumer intentions towards digital marketing of agricultural products are influenced by various factors and digital marketing can positively impact agricultural sales. Dlodlo & Dhurup (2013) revealed that

1- Calculated using an annual population growth rate of 1.06% from the 2016 census figure of 736,224 (Statistical Centre of Iran, 2016) small-scale farmers who adopted digital marketing strategies experienced boosted sales and market reach. Furthermore, Lu *et al*. (2016) found that social media marketing improved brand awareness and customer engagement for organic agricultural products. However, beyond increasing sales and engagement, consumer trust plays a crucial role in shaping online purchasing decisions.

Yadav & Rahman (2017) reported that social media marketing activities positively affected customer equity and purchase intention for agricultural products. Trust has emerged as a critical factor in shaping consumer intentions towards the digital marketing of these products. Kang & Namkung (2019) demonstrated that trust in online platforms and sellers significantly influenced consumers' willingness to purchase agricultural products through e-commerce channels. This finding aligns with earlier research by Pavlou & Fygenson (2006), who emphasized the role of trust in reducing perceived risks associated with online transactions. Building on this, various psychological and technological factors further shape consumer trust and purchasing behavior in different regions.

Research in Saudi Arabia emphasizes the impact of social influence, hedonic motives, perceived risk, perceived usefulness, information quality, and perceived ease of use on trust and continuance intention, ultimately leading to sustainable consumer behavior (Zia *et al*., 2022). Additionally, the performance of e-marketplaces, perceived ease of use, and perceived benefits play a crucial role in influencing consumer purchase intentions for agricultural products online, with website convenience being a significant factor (Kusumawati *et al*., 2022). Furthermore, in China, factors like perceived interactivity, perceived endorsement, product familiarity, subjective norms, altruistic value, and livestream shopping experience significantly affect consumers' attitudes and purchase intentions towards agricultural products via public-interest livestreaming, especially during the COVID-19 pandemic (Yu & Zhang, 2022). These findings demonstrate that while consumer trust, psychological and technological factors play a vital role, individual preferences, cultural influences, and economic conditions further shape digital purchasing behaviors across different regions.

Studies in Indonesia and India highlight the significance of consumer behavior, subjective norms, demographic variables, time savings, convenience, and promotional attributes in shaping online purchasing intentions for agricultural products (Aulia *et al*., 2024; Masih *et al*., 2024). These factors suggest that digital marketing strategies must be tailored to local consumer preferences and market dynamics to enhance engagement and sales.

Researches in Iran has shed light on the significance of digital agricultural marketing. Sharifpour *et al*. (2016) highlighted the crucial role of social media in shaping consumer perceptions and facilitating direct interactions between consumers and agricultural brands, thereby augmenting engagement intentions. Despite these opportunities, addressing existing barriers, it is essential to maximizing the potential of digital agricultural marketing in Iran. Alavion & Taghdisi (2021) introduced the Geographic Model of Planned Behavior (GeoTPB) to analyze the adoption of e-marketing in rural areas. Their study, which encompassed 1,000 villages, successfully predicted 76% of villagers' intentions to adopt e-marketing and identified six distinct rural clusters. Notably, the traditionally less developed southern and southeastern provinces emerged as leading regions for e-marketing adoption, challenging conventional assumptions and providing valuable insights for targeted rural development strategies.

Building on this review, consumer intention to engage with digital marketing for agricultural products is shaped by several key factors. Perceived usefulness and ease of use significantly enhance the likelihood of online purchases, as consumers are more inclined to utilize digital platforms, they deem beneficial and user-friendly. Trust in online platforms and sellers is essential, as it mitigates perceived risks and increases willingness to transact. Furthermore, social influence and social media marketing play a pivotal role in boosting brand awareness and engagement, which further drives purchase intentions. Additionally, the quality of information, website performance, and convenience are crucial in shaping consumer decisions. Subjective norms, demographic variables, and behavioral factors- such as time savings and promotional attributes- also impact online purchasing intentions, highlighting the multifaceted nature of consumer engagement with digital marketing in agriculture. To the best of our knowledge and based on the reviewed literature, this study represents the first investigation within the agricultural sector in Iran. The objective of this research is to examine the key factors influencing the intention to adopt digital marketing for agricultural products in Urmia City.

Methodology

Research Design and Sampling Methods

In this study, we employed a quantitative research design to investigate the intentions of consumers in Urmia toward engaging with the digital marketing of agricultural products. Specifically, a cross-sectional survey methodology was employed to collect data from a sample of consumers.

This study utilized a structured questionnaire to gather cross-sectional data on factors influencing digital marketing engagement in agriculture. The questionnaire encompassed three main groups of variables: (1) Perceptions and Trust, including perceived usefulness (PU), perceived ease of use (PEOU), trust (TR), information quality (IQ), and social influence (SI); (2) Demographic and Economic Factors, comprising age (AGE), education level (EDU), income (INC), and price sensitivity (PS); and (3) Experience and Behavioral Intention, covering prior online purchase experience (EXP) and the intention to engage with digital marketing of agricultural products. To ensure a representative sample, we employed a multi-stage sampling technique, selecting regions based on agricultural activity and accessibility, and then randomly choosing participants from lists provided by local agricultural associations. Following data cleaning to address incomplete or inconsistent responses, we analyzed a final sample of 385 valid questionnaires.

The target population for the study was general consumers in Urmia who have the potential to purchase agricultural products. The sample size was determined using the Cochran's formula (1977), which resulted in a sample of 385 respondents.

$$n_0 = \left(Z^2 \times p \times q\right) / e^2 \quad (1)$$

Where n_0 is the sample size, Z = 1.96 (95% confidence level), p = 0.5 (most conservative estimate) and e = 0.05 (desired level of precision). This calculation yielded an initial sample size of 385. Cluster random sampling method was used. The city of Urmia is divided into 5 municipal districts, each of which was considered as a cluster.

The structured questionnaire was pilot tested with a small sample of consumers to ensure the clarity and validity of the items. Based on the pilot results, minor revisions were made to the wording of specific questions.

The questionnaire is structured into five distinct sections. Section A collects demographic information, including age, education level, and income level. Section B focuses on participants' online shopping experience, encompassing purchase history and shopping frequency. Section C assesses perceptions and attitudes, measuring constructs such as perceived usefulness, perceived ease of use, trust, information quality, social influence, and price sensitivity. Section D evaluates engagement intention, capturing metrics related to future use likelihood and recommendation intent. Finally, Section E provides space for additional comments, allowing participants to share desired features and express any concerns regarding online shopping platforms.

Data were collected over a 4-week period through face-to-face interviews with respondents in various locations across Urmia, including local markets, grocery stores, and community centers. In total, 384 valid responses were obtained. Respondents, while not necessarily the designated head of household, were identified as the primary household shoppers.

Theoretical and Analytical Framework

The theoretical foundation of this study is anchored in the neoclassical microeconomic theory, which posits that economic agents seek to maximize their utility when making decisions. In the context of this research, this theory is applied to understand consumer intentions regarding the digital marketing of agricultural products. Specifically, the study employs the Random Utility Model (RUM) to conceptualize how consumers decide to engage with digital marketing platforms. According to RUM, a consumer's intention to engage with digital marketing is influenced by the utility derived from such engagement.

Consumers are assumed to evaluate the utility (U) of engaging with digital marketing versus not engaging based on factors like perceived usefulness, ease of use, trust, and social influence. The choice to engage with digital marketing is made if the utility from engaging exceeds the utility from not engaging. Formally, a consumer will opt to engage with digital marketing if and only if $Uj > Uk$, where j and k represent digital marketing and an alternative choice, respectively. The consumer utility i (U_i) is decomposed into a deterministic component (V_i), which includes measurable factors, such as perceived benefits and ease of use, and a random component (ε_i), which captures unobservable factors affecting the consumer's decision (Greene, 2019). This theoretical framework guides the empirical analysis, which uses an econometric logit model to estimate the probability of consumer engagement with digital marketing, based on the specified utility components.

$$U_i = V_i + \varepsilon_i \quad (2)$$

If individual *i*'s utility from choosing a digital purchase exceeds that of a non-digital purchase, the variable *z* will equal one; otherwise, it will equal zero (McFadden, 1974).

$$Z_i = (U_{ij} - U_{ik}) \rightarrow \begin{cases} if\ (U_{ij} - U_{ik}) \geq 0\ then\ Z_i = 1 \\ if\ (U_{ij} - U_{ik}) < 0\ then\ Z_i = 0 \end{cases} \quad (3)$$

Let U_{ij} denote the utility that consumer *i* derives from selecting digital marketing option (j), and U_{ik} represent the utility from choosing an alternative option. The variable Z_i is defined as the dependent variable that captures the difference in utilities. Specifically, Zi takes a value of one if the difference in utilities is positive, and zero otherwise. Thus, the utility difference model simplifies the choice process into a binary outcome, reflecting whether the digital marketing option is favored over the alternative based on the comparative utility values.

To empirically analyze the factors influencing Z_i, the following logistic regression model is employed (Greene, 2019):

$$\log itP(Z_i = 1) = \alpha + \beta X_i + \varepsilon_i \quad (4)$$

where, logitP(Z_i = 1) denotes the log odds of Z_i equating to one, thereby indicating a preference for digital marketing option j. X_i represents a vector of control variables that could potentially influence the consumer's choice, encompassing demographic characteristics, prior experience, and other pertinent factors. The terms α and β correspond to the intercept and the coefficient for the control variables, respectively. ε_i signifies the error term, encapsulating unobserved factors that may impact the decision-making process. The Logit model can be estimated using maximum likelihood (MLE) process. The MLE of the logit model involves finding parameter estimates that maximize the likelihood function, which is derived from the probability distribution of the logistic function. This approach ensures that the estimated coefficients best fit the observed data by maximizing the probability of obtaining the observed outcomes, as discussed by McFadden (1974) and Greene (2019).

The marginal effect (ME) measures the change in the probability of Z_i=1 resulting from a one-unit change in X_i. The probability P(Z_i=1) is given by the logistic function:

$$P(Z_i = 1) = \frac{1}{1 + exp[-(\alpha + \beta X_i)]} \quad (5)$$

To compute the marginal effect of X, we differentiate the probability function with respect to X:

$$ME = \frac{\partial P(Z_i = 1)}{\partial X} = P(Z_i = 1) \cdot (1 - P(Z_i = 1)) \cdot \beta \quad (6)$$

Standard errors for the marginal effects can be computed using the delta method or bootstrapping techniques. Estimating marginal effects is crucial for evaluating how incremental changes in predictors, such as perceived usefulness or trust, affect consumer engagement. Such insights are instrumental in enabling marketers to refine strategies, thereby enhancing the overall efficacy of digital marketing initiatives.

Descriptive Statistics

Table 1 summarizes the dependent and independent variables utilized in this study. Following previous studies, we grouped the explanatory variables into three components: (1) Perceptions and Trust; (2) Demographic and Economic Factors; and (3) Experience. Stata (ver. 17.0, Stata Corp) is used for estimations. To address potential heteroskedasticity arising from measurement errors, model specification inaccuracies, or subpopulation variances, we employed the 'robust' option in Stata to obtain robust standard errors for the logit model estimates. Furthermore, an analysis of variance decomposition of the parameters facilitated the evaluation of multicollinearity among the predictors.

Table 1 presents the summary statistics for the variables employed in this investigation. The dependent variable, intention to engage (Y), indicates that 65% of respondents expressed an intention to engage with digital marketing initiatives for agricultural products, underscoring a strong inclination to interact with such efforts, which is essential for understanding consumer behavior in this context. Among the independent variables, PU and PEOU exhibited mean scores above the midpoint of the scale, indicating that respondents generally find digital marketing of agricultural products useful and easy to navigate, which is essential for user adoption and sustained engagement. TR and IQ demonstrated moderate to positive levels, suggesting that respondents possess a fair to good level of trust and find the information provided reliable and of good quality, both of which enhance user experience and engagement. Notably, PS had the highest mean among the Likert-scale variables, indicating that price is a significant factor for respondents considering engagement with digital marketing for agricultural products. Demographic analysis revealed a mean age of 42.3 years, with respondents' ages ranging from 18 to 75 years, indicating a wide range of age distribution. EDU and INC recorded means near the midpoints of their respective scales, indicating a varied educational background and broad representation of different income levels within the sample, thereby contributing to the robustness of the study's conclusions. Finally, 78% of respondents reported having prior online purchase experience, indicating a high familiarity with online shopping, which may influence their intention to engage with digital marketing of agricultural products by enhancing confidence and reducing perceived risks.

Results

Logit Model Results

To examine the factors influencing consumers' intentions to engage with digital marketing of agricultural products, we estimated a logit model. Table 2 presents the results of this estimation.

As shown in Table 2, the logistic regression model exhibits strong overall fit, as indicated by the likelihood ratio chi-square test statistic of 218.73, which is highly significant ($p < 0.000$). This result provides compelling evidence for the statistical significance of the model as a whole, suggesting that independent variables collectively explain substantial explanatory power for the variance observed in the dependent variable.

Table 1- Descriptive Statistics of Variables

Variable	Definition of the variables	Variables type	Mean (SD)
Intention to Engage (Y)	The intention to engage with digital marketing initiatives of agricultural products	Binary (1 = Yes, 0 = No)	0.65 (0.48)
Perceived Usefulness (PU)	The degree to which a person believes that using digital marketing for agricultural products enhance their purchasing performance.	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)	
Perceived Ease of Use (PEOU)	The degree to which a person believes that using digital marketing for agricultural products is free of effort.	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)	
Trust (TR)	The extent to which consumers believe in the reliability and integrity of digital marketing platforms for agricultural products.	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)	
Information Quality (IQ)	The perceived quality of information provided through digital marketing channels for agricultural products.	5-point Likert scale (1 = Very Poor, 5 = Excellent)	
Social Influence (SI)	The degree to which an individual perceives that important others believe they should use digital marketing for purchasing agricultural products.	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)	)
Price Sensitivity (PS)	The degree to which consumers focus on paying low prices for agricultural products.	5-point Likert scale (1 = Not at all sensitive, 5 = Extremely sensitive)	
Age	The age of the respondents	Continuous variable (in years)	42.3 (13.7)
Education Level (EDU)	The highest level of education attained by the respondent	Categorical (1 = Primary, 2 = Secondary, 3 = Bachelor's, 4 = Master's, 5 = Doctorate)	
Income (INC)	The monthly income level of the respondent	Categorical (1 = Low, 2 = Medium-Low, 3 = Medium, 4 = Medium-High, 5 = High)	
Prior Online Purchase Experience (EXP)	Whether the respondent has previous experience with online purchasing	Binary (1 = Yes, 0 = No)	

Table 2- Estimated Logit Model Results

Variable	Coefficient (p-value)	Marginal Effect (p-value)
Constant	-3.241 (0.000)	-
Perceived Usefulness (PU)	0.652 (0.000)	0.162 (0.000)
Perceived Ease of Use (PEOU)	0.438 (0.000)	0.109 (0.000)
Trust (TR)	0.521 (0.000)	0.129 (0.000)
Information Quality (IQ)	0.375 (0.001)	0.093 (0.001)
Social Influence (SI)	0.289 (0.002)	0.072 (0.002)
Price Sensitivity (PS)	-0.203 (0.053)	-0.050 (0.055)
Age	-0.015 (0.032)	-0.004 (0.046)
Education Level (EDU)	0.241 (0.039)	0.060 (0.039)
Income (INC)	0.185 (0.037)	0.046 (0.037)
Prior Online Purchase Experience (EXP)	0.729 (0.002)	0.181 (0.002)
LR $chi^2(10)$ = 218.73 (0.0000)	Pseudo R^2 = 0.2453	PRP = 76%

Source: Research findings

The robustness of this finding supports the relevance of the chosen predictors in capturing the underlying dynamics of consumers' intentions to engage with digital marketing of agricultural products.

The model's explanatory power is reflected in the McFadden's Pseudo R^2 value of 0.2453, indicating that approximately 24.53% of the variation in the dependent variable is explained by the predictors. While this value may not account for all variance, it is considered a substantial level of explanatory power for behavioral models in social sciences (McFadden, 1974). This finding highlights the pertinence and efficacy of the selected variables in elucidating the underlying mechanisms driving consumer intentions in this context. Further supporting the model's robustness is the Percentage of Right Prediction (PRP) of 76%. This metric indicates that the model accurately classifies more than three-quarters of the cases, showcasing its strong predictive capability (Wooldridge, 2010). Such a high PRP reinforces the model's utility as a tool for understanding and forecasting consumer behavior specifically within the domain of digital marketing for agricultural products. The model's predictive accuracy also enhances its potential applications in both theoretical frameworks and practical marketing strategies. The following provides an analysis of how each factor influences the intention to engage digital marketing for agricultural products, along with the degree of their effect.

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), consistent with the Technology Acceptance Model (TAM) (Davis, 1986), demonstrate statistically significant positive effects on engagement intentions, with marginal effects showing that a one unit increase in these variables is associated with 16.2% and 10.9% increases in the likelihood of engagement, respectively. The results of the study conducted by Ashraf *et al*. (2016) are consistent with the findings of our research, demonstrating that PU and PEOU play a crucial role in enhancing the overall user experience; and the study by Al-Gasawneh *et al*. (2022) demonstrates that these variables exert a positive influence on post-purchase behavior among Jordanian consumers.

Trust (TR), another significant predictor, reveals that higher trust levels increase engagement probability by 12.9%. This result aligns with extant literature emphasizing the pivotal role of trust in digital marketing environments (Gefen *et al*., 2003), particularly within agriculture where product authenticity is critical. Similarly, Rai & Timalsina (2024) emphasize trust as a central factor in enhancing marketing effectiveness, noting that it fosters consumer engagement and strengthens brand relationships. The study by Otopah *et al*. (2024) also demonstrates that consumer trust moderates the relationship between digital marketing and consumer engagement.

Information Quality (IQ) also exerts a significant positive influence, with a one-unit increase leading to a 9.3% rise in engagement likelihood, all other conditions remain constant, consistent with the Information Systems Success Model (DeLone & McLean, 2003). It underscoring the critical role of reliable and pertinent information in shaping consumer decision-making processes within this context. The findings of this research align with the results of the study by Surjandy & Cassandra (2022), which demonstrate that high-quality information positively influences buying decisions by mitigating perceived risks.

Social Influence (SI), aligned with the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al*., 2003), similarly affects engagement, with a marginal effect of 7.2%, all other conditions remain constant, emphasizing the importance of peer influence in the adoption of digital marketing channels. The research conducted by Wang & Huang (2022) elucidates that digital influencers exert a substantial impact on consumer engagement and purchase behavior within online social commerce communities by leveraging diverse forms of social power.

Price Sensitivity (PS) shows a marginally significant negative relationship with engagement, suggesting that highly price-sensitive consumers may be less likely to use digital platforms, even though this effect approaches but does not meet conventional significance levels ($p = 0.053$). This finding contributes to the ongoing discourse on the role of price perceptions in digital marketing engagement (Lichtenstein *et al*., 1993) and may have implications for pricing strategies in this sector. Hidrobo *et al*. (2021) also demonstrates that farmers in Ghana, though highly price-sensitive, are largely willing to pay a low monthly fee for a digital platforms. The marginal effects analysis reveals an inverse relationship; a unit increase in Price Sensitivity corresponds to a 5% decrease in engagement probability, ceteris paribus. This finding suggests that highly price-sensitive consumers may be less inclined to engage with digital marketing channels for agricultural products.

Demographic variables like age, education, and income also play important roles. Age is negatively associated with engagement, although its effect is relatively small (0.4% decrease per year). This finding aligns with extant literature on digital divide and technology adoption across age groups (Czaja *et al*., 2006). In contrast, higher education levels and income both positively influence engagement, with marginal effects of 6% and 4.6%, respectively. These results corroborate previous research indicating that higher levels of education and income are associated with increased digital technology adoption and online consumer behavior (Hargittai & Hinnant, 2008). Such findings may have implications for market segmentation and targeted marketing strategies in the agricultural sector.

Prior online purchase experience emerges as a particularly strong predictor, increasing engagement likelihood by 18.1%, ceteris paribus, highlighting the importance of familiarity and prior behavior in shaping future engagement. A phenomenon well-documented in consumer behavior literature (Ajzen, 2002). The magnitude of this effect suggests that consumers with previous online shopping experience are substantially more likely to engage with digital marketing platforms for agricultural products, highlighting the potential value of cross-sector marketing initiatives and the transfer of online shopping behaviors across product categories. The study by Yi *et al*. (2024) indirectly reflects the influence of prior experiences, as familiarity with a product or service often shapes perceptions of quality and value, thereby affecting satisfaction levels.

Discussion and Conclusion

This study examined the factors influencing consumer intentions to engage with digital marketing of agricultural products in Urmia, Iran, utilizing a logistic regression model to analyze data from 385 respondents. The findings provide valuable insights into the complex interplay of factors shaping consumer behavior in this context, with implications for both theory and practice. The results strongly support the relevance of key constructs from established theoretical frameworks, particularly in the domain of digital agricultural marketing. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) were identified as significant positive predictors of engagement intention. Trust (TR) also emerged as a significant determinant of consumer engagement. In agricultural markets, where product quality and authenticity are paramount concerns, trust-building mechanisms such as transparency in sourcing, product certifications, and consumer reviews, are likely crucial in overcoming consumer hesitations related to product quality in the digital marketplace. Moreover, the significant positive effect of Information Quality (IQ) on engagement, highlighting the critical role of reliable and pertinent information in shaping consumer decision-making processes within this domain.

The positive effect of Social Influence (SI) on engagement emphasizes the importance of social factors in technology adoption. This finding suggests that digital marketing strategies in agriculture should leverage social proof and community engagement to enhance effectiveness. Demographic factors reveal nuanced effects, with engagement intention. Age showed a small but significant negative association with engagement intention. In contrast education level and income demonstrated positive relationships, more educated consumers are more likely to interact with digital marketing platforms for agricultural products. These findings emphasize the need for tailored marketing approaches that account for age-related barriers while leveraging the greater digital readiness of more educated and affluent segments.

A key insight is the strong positive association between Prior Online Purchase

Experience and engagement intentions. This suggests that prior familiarity with online shopping significantly enhances the likelihood of engaging with digital agricultural platforms. This finding highlights the potential synergies between general e-commerce experiences and specific engagement with digital agricultural marketing.

For agricultural marketers, the results underscore the importance of designing user-friendly digital platforms that provide clear, tangible value to consumers. Trust-building measures, such as strong security protocols and verified customer reviews, are crucial in an industry where product authenticity and quality are key. Furthermore, digital marketing initiatives should emphasize high-quality, educational content that informs consumers about product origins, farming practices, and sustainability to increase efficacy. Marketers should take advantage of social proof and community involvement. Campaigns must be customized for various demographic groups, taking into account differences in participation across age, income, and educational levels. Addressing price sensitivity is another important consideration. Marketers could experiment creative pricing techniques and unambiguous value communication. Lastly, utilizing customers' past online shopping experiences-possibly by forming alliances with well-known e-commerce platforms-can stimulate interest in agricultural product digital marketing.

This study makes a valuable contribution to the literature by providing empirical evidence on consumer intentions towards digital marketing of agricultural products in a developing country, addressing a notable gap in current research. It integrates multiple theoretical frameworks to percent a comprehensive model of consumer behavior in this specific domain. Notably, the examination of price sensitivity and prior online purchase experience bridges insights from general e-commerce literature with the specific domain of agricultural product marketing.

In conclusion, this study provides valuable insights for practitioners and scholars in the field of digital agricultural marketing. As this domain continues to evolve, ongoing research will be essential to ensure that technological advancements in agricultural marketing contribute positively to broader societal goals while meeting the changing needs and expectations of consumers.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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نشریه اقتصاد و توسعه کشاورزی
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مقاله پژوهشی

جلد ۳۹، شماره ۲، تابستان ۱۴۰۴، ص. ۱۶۴-۱۵۱

بازاریابی دیجیتال محصولات کشاورزی: عوامل مؤثر بر تمایل مصرف‌کنندگان در ارومیه، ایران

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تاریخ دریافت: ۱۴۰۳/۱۰/۲۰
تاریخ پذیرش: ۱۴۰۳/۱۲/۰۴

چکیده

با توجه به رشد شتابان پلتفرم‌های دیجیتال و تغییر بنیادین روش‌های بازاریابی، بررسی میزان تمایل مصرف‌کنندگان به استفاده از بازارهای دیجیتال در بخش کشاورزی از اهمیت ویژه‌ای برخوردار است. این مطالعه به بررسی عوامل مؤثر بر تمایل مصرف‌کنندگان به استفاده از بازاریابی دیجیتال محصولات کشاورزی در شهر ارومیه می‌پردازد. داده‌ها از طریق پرسشنامه ساختاریافته از ۳۸۵ پاسخ‌دهنده جمع‌آوری و با استفاده از مدل رگرسیون لوجیت تحلیل شدند. نتایج نشان می‌دهد که مفید بودن، سهولت استفاده، اعتماد، کیفیت اطلاعات و تأثیر اجتماعی به‌طور معنادار و مثبتی بر تمایل مصرف‌کنندگان تأثیر دارند. همچنین، عوامل جمعیت‌شناختی نظیر سن (با اثر منفی)، سطح تحصیلات و درآمد (هر دو با اثر مثبت) نقش مهمی ایفا می‌کنند. تجربه قبلی خرید آنلاین یکی از مهمترین عوامل تاثیرگذار بر تمایل می‌باشد و حساسیت به قیمت تأثیر منفی نسبتاً معناداری دارد. این مطالعه با ارائه شواهد تجربی از یک کشور در حال توسعه و مدل جامعی برای درک رفتار مصرف‌کننده در بازاریابی دیجیتال کشاورزی، به ادبیات موجود کمک می‌کند. از جمله پیامدهای این مطالعه برای بازاریابان می‌توان به طراحی پلتفرم‌های کاربرپسند، اولویت دادن به سازوکارهای ایجاد اعتماد و تدوین راهبردهای متناسب با ویژگی‌های جمعیت‌شناختی مختلف اشاره کرد.

واژه‌های کلیدی: ارومیه، بازاریابی دیجیتال، محصولات کشاورزی، نیت مصرف‌کننده،

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https://doi.org/10.22067/jead.2025.91586.1325

Journal of Agricultural Economics & Development

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

Research Article
Vol. 39, No. 2, Summer 2025, p. 165-180

Simultaneous Evaluation of Technical Efficiency and Production Risk of Rice Paddy Fields

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Received: 13-01-2025 Revised: 15-04-2025 Accepted: 16-04-2025 Available Online: 16-04-2025	**How to cite this article:** Kazmi Shabanzade Aflaki, H., Javanbakht, O., & Alefi, Kh. (2025). Simultaneous evaluation of technical efficiency and production risk of rice paddy fields. *Journal of Agricultural Economics & Development, 39*(2), 165-180. https://doi.org/10.22067/jead.2025.91636.1327

Abstract

Agricultural activities are inherently riskier than other types of production and are often accompanied by inefficiencies. Therefore, studying risk and inefficiency simultaneously can help enhance productivity. The statistical population in this study consisted of rice farmers in Rasht County. Based on data from the Agricultural Jihad Organization of Guilan province (2016), the total number of farmers at the time of the study was 38,763. Using Cochran's formula, the required sample size was calculated to be 226, representing approximately 58 percent of the population. The questionnaire consisted of two parts: one focusing on the inputs used in the rice production process, and the other on the socio-economic characteristics of farmers and their farms. To simultaneously evaluate the technical efficiency and production risk of rice farmers in Rasht County in 2018, a generalized Stochastic Frontier Production (SFP) model with flexible risk properties was employed. The results of estimating production risk function showed that (i) rice production was significantly affected by land, seed and labour inputs; (ii) land, water, age, and gender variables were risk-increasing factors; (iii) seed, herbicides, machinery, farmer's education, family size, and farming experience were risk-reducing inputs; (iv) seed, labour, membership in the agricultural cooperatives and insurance increased technical inefficiency; and (v) nitrogen fertilizer, water, gender, experience, and participation in educational and promotional programs reduce technical inefficiency in the studied area. The results of estimating technical efficiency showed that the average technical efficiency of the rice paddy field was 93.47 percent and 96.27 percent with and without a risk component, respectively. Therefore, it is clear that estimating the model without a risk component leads to biased results of technical efficiency. In conclusion, it is recommended that the risk component be considered when measuring the technical efficiency of paddy fields to achieve sound risk management and highly efficient production.

Keywords: Agricultural inputs, Production risk, Rice farming, Risk management, Stochastic frontier model, Technical efficiency

JEL classifications: *M11, O13, Q12.*

Introduction

The assessment of the efficiency of agricultural production is an important issue in the process of development in countries. The agricultural sector is considered a high-risk activity, influenced by a variety of factors such as climatic conditions, pests and diseases, fluctuations in input and output prices, financial uncertainties, human-related risks, and

https://doi.org/10.22067/jead.2025.91636.1327

production input risks. Production inputs contribute to the risk intensity by introducing uncertainty in terms of availability, cost fluctuations, quality variability, and their interaction with environmental conditions, all of which can significantly affect overall farm performance and profitability. Tveteras (1999) express two main reasons for considering production risk in inputs to examine the behavior and productivity of farms. First, risk-averse producers choose the amounts of inputs that are different from the optimal level inputs that are chosen by risk-neutral producers. Second, when the risk-averse producers tend to adopt new technologies, they consider its risky aspects. Therefore, they may choose technology that has a high production average. According to Bokusheva & Hockmann (2006), the risk not only affects production but also influences the producers' behavior mainly on inputs usage. So, when farmers consider risk management and decrease the risk in their decisions, changes in the amount and manner of using inputs may change significantly the technical efficiency. Studies have shown that the effect of risk on production can be investigated through the effect of inputs selection on production variance, because, some inputs increase output variance whilst some others reduce it. Just & Pope (1978) have promoted the conventional approach of econometrics to evaluate the production risk. The implicit assumption of their model is the lack of inefficiency in the production units (farms). While the surveys show that these units are usually inefficient, researchers have concluded that for the simultaneous study of efficiency and risk, SFP models could be combined with the Just and Pope model (Jaenicke *et al.*, 2003). For example, Battese *et al.*, (1997) used stochastic frontier analysis (SFA) with heteroscedastic error terms to define the efficiency of small farmers in Ethiopia. Kumbhakar (1993, 2002) also applied this method to specify the efficiency and risk preferences of Swedish dairy farms and Norwegian salmon producers. Jaenicke *et al.*, (2003) applied an SFA model with a heteroscedastic error term to compare technical efficiency and risk in different cotton cropping systems. Villano & Fleming (2006) used the methods to rainfed lowland rice farms in the Philippines. Bokusheva & Hockmann (2006) take up this combined approach to evaluate the efficiency of Russian arable farms. Sarker *et al.* (2016) studied production risk and technical efficiency in Thai koi farming by the Just & Pope framework extended to the stochastic frontier model (SFM) by Kumbhakar (2002). Lemessa *et al.* (2017) analysed the technical efficiency and production risk of 862 maize farmers in Ethiopia using the stochastic frontier approach with flexible risk properties. Also, the other studies done in this field can mention to Oppong *et al.* (2016), Yang *et al.* (2016), Agustina (2016), Baawuah (2015), Adinku (2013), Tiedemann & Latacz-Lohmann (2013), Ogunniyi & Ojedokun (2012) and Villano *et al.*, (2005).

In Iran, a limited number of studies have simultaneously evaluated technical efficiency and production risk, including the study by Esfandiari *et al.*, (2013) (Determining technical efficiency and rice production risk in Marvdasht County, Fars province); Alikhani *et al.* (2015) (Evaluation of technical efficiency and production risk of cold-water fish farms in Kurdistan province) and Hosseinzad & Alefi (2016) (Evaluation of technical efficiency and production risk of potato farmers in Ardabil province).

The literature shows that a production function that takes into account the effects of inputs on both production risk and technical efficiency simultaneously is considerably better able to reflect production technology than a simple analysis of efficiency. Rice is the second most important food after wheat for Iranian people. Guilan province in the north of Iran is one of the important rice-producing provinces. This province has 238,544 hectares of cultivated area and 1,104,551 tons of paddy production. Rasht County also has the largest cultivated area and the largest production of this product among the counties of Guilan province, with 51,039 hectares of cultivated area and 226,155 tons of paddy production (Statistical Yearbook of Guilan province, 2022). Given the significant volume of rice production in Guilan province and especially Rasht County, a scientific study of the various dimensions of production risk and technical efficiency for making better use of existing facilities and helping planners and decision makers seems logical. Therefore, this study has examined two essential concepts in agricultural economics (technical efficiency and production risk) in an integrated model, unlike traditional methods that examine technical efficiency and production risk separately. Incorporating the production risk helps to obtain unbiased estimates of the technical efficiency. It also investigates production risk, technical efficiency, and factors associated with rice production of smallholder farmers. Thus, rice production variability is assessed from two perspectives: production risk and technical efficiency.

Materials and Methods

Theoretical Framework

The method of analysis proposed for this study is consistent with the stochastic frontier approach, which was independently proposed by Aigner *et al.*, (1977) and Meeusen & Vanden Broeck (1977). This model proposes that inputs have a similar effect on mean and variance outputs. But Just & Pope's (1978) production function proposed separate effects of the inputs on the mean and variance outputs, whilst Kumbhakar (2002) further incorporates the technical inefficiency model. Following Kumbhakar (2002), the production process is represented below as equation 1.

$$y_i = f(x_i; \alpha) + g(x_i;\ \beta)v_i - q\left(x_i; z_j; \gamma\ \right)u_i \tag{1}$$

where, y_i refers to the observed output produced by the i-th farm, $f(x_i;\ \alpha)$ is the deterministic output function, $g(x_i;\ \beta)$ is the output risk function, β's are the to be estimated coefficients of production risk function, x_i are the inputs variables, α's are the to be estimated coefficients of the mean output function, $q(x_i;\ z_j;\ \gamma)$ represents the technical inefficiency model, γ's are the to be estimated parameters in the technical inefficiency model, v_i is the random noise, representing production risk and u_i denotes farm specific technical inefficiencies. Given the values of the inputs, the inefficiency effects, u_i, the mean output of the *i-th* farmer is given by equation 2:

$$E(y_i|x_i\,.u_i) = f(x_i; \alpha) - g(x_i; \beta)u_i \tag{2}$$

Technical efficiency of the i-th farm is the ratio of observed output given the values of its inputs and its inefficiency effects to corresponding maximum feasible output if there were no inefficiency effects (Battese & Coelli, 1988). The technical efficiency of the i-th farm is given by equation 3, which is consistent with Kumbhakar (2002) specification of technical efficiency:

$$TE_i = \frac{E(y_i|x_i\,.u_i)}{E(y_i|x_i\,.u_i = 0)} = \frac{f(x_i; \alpha) - g(x_i; \beta)u_i}{f(x_i; \alpha)} = 1 - \frac{g(x_i; \beta)u_i}{f(x_i; \alpha)} \tag{3}$$

And technical efficiency becomes as equation 4.

$$TE_i = 1 - TI_i \tag{4}$$

The technical inefficiency (TI), is represented as equation 5.

$$TI_i = \frac{g(x_i\,;\ \beta)u_i}{f(x_i\,; \alpha)} \tag{5}$$

The variance of output or production risk is given by equation 6.

$$\text{var}\ (y_i|x_i\,.u_i) = g^2(x_i\,;\ \beta) \tag{6}$$

The marginal effect of the input variables on the production risk is given as equation 7.

$$\frac{\partial \text{var}(y_i)}{\partial x_i} = \frac{\partial g^2(x_i\,;\ \beta)}{\partial x_i} = 2\text{g}(x_i\,;\ \beta).\,g_i(x_i\,;\ \beta) \tag{7}$$

The marginal effect of the i-th input on production risk is positive or negative depending on the signs of g(x_i; β), and g_i(x; β), where the latter is the partial derivative of the production risk function with respect to the i-th input. If the marginal risk is positive, it means that input is risk increasing and if the marginal risk is negative, it means that the input is a risk decreasing. Based on the distributional assumptions of the random errors a log likelihood function for the observed farm output is parameterized in terms of $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\lambda = \frac{\sigma_u^2}{\sigma_v^2} \geq 0$ (Aigner *et al.*, 1977).

Empirical Model Specification

The empirical application of this study is consistent with models developed by Kumbhakar (2002), Aigner *et al.*, (1977), Meeusen & Vanden Broeck (1977) and Just & Pope (1978). Deterministic part of the production frontier in equation 1 assumed a Translog model in equation 8.

$$lny = \alpha_0 + \sum_{i=1}^{n} \alpha_j lnx_{ij} + 0.5\sum_{i=1}^{n}\sum_{k=1}^{n}\alpha_{jk} lnx_{ij} lnx_{ki} + \varepsilon_i \quad (8)$$

α_j's denote the unknown true values of the technology parameters. If, $\alpha_{jk}=0$ then the Translog stochastic frontier model reduces to Cobb-Douglas model specified as equation 9.

$$lny_i = a_0 + \sum_{j=1}^{n} a_j lnx_{ji} + \varepsilon_i \quad (9)$$

The error term is specified as equation 10.

$$\varepsilon_i = g(x_i;\ \beta)v_i - q(\,x_i\ ; z_j\ ; \gamma)u_i \quad (10)$$

Production Elasticity and Return to Scale

The sensitivity of a variable towards changes another variable is defined as elasticity. The concept of elasticity can be applied to the production function so as to determine the stage of production in which the rice farmers are operating. The Translog production function elasticities are a function of the level of input consumption to different inputs. They are expressed as equation 11.

$$\frac{\partial lnE(y_i)}{\partial lnx_{ji}} = a_j + a_{jj} lnx_{ji} + \sum_{k\neq 1} a_{jk} lnx_{ki} \quad (11)$$

A summation of the partial elasticities of the various input variables to output is a measure of the return to scale (RTS).

If RTS> 1 → Increasing returns to scale (IRS);

If RTS <1 → Decreasing returns to scale (DRS) and,

If RTS = 1 → Constant returns to scale (CRS).

Also, in equation 8, output and input variables have been normalized by their respective means.

Studies, investigated the effect of inputs on production risk in Iran using Just & pope model (1978) such as Mehri *et al.*, (2020), Yazdani & Sassuli (2008), Karbasi *et al.*, (2005), Sharzehei & Zibaei (2001), showed that a little percentage of production risk was related to production inputs (due to the low amount of the coefficient of determination and the adjusted coefficient of determination of the production risk function). So they concluded that various factors such as the geographical location of the farm, the age of the farmer, the level of education and experience, the farmer's gender, access to credit, extension services, rainfall and type of soil were all effective on production risk, and the lack of these variables in the model resulted in a lower coefficient of determination. Therefore, in the present study, in addition to the effects of inputs on production risk, the effect of factors such as farmers' age, education level (edu), experience (exper), gender (gen), marriage status (mar) and household size (fam size) are also considered in the production risk. The linear production risk function is specified as Equation 12.

$$g(x_i;\ \beta)v_i = \beta_0 + \sum_{i=1}^{n} \beta_i\, x_i \quad (12)$$

Where, x_i's represent the input variables; β's are the unknown true coefficients of the risk model parameters and v_i's are the pure noise effects. In production risk function, in addition to the effects of inputs on the production risk, the effect of a number of other variables (as already mentioned) is considered. If β's becomes negative, the respective input reduces output variance and vice versa (Just & Pope, 1978).

The technical inefficiency effects were given by Equation 13.

$$q(x_i; z_j\ ; \gamma) = \gamma_0 + \sum_{i=1}^{n} \gamma_i x_i + \sum_{j=1}^{n} \gamma_j z_j \quad (13)$$

Where, x_i's represent the input variables and z_j's are exogenous (socio-economic) variables; γ denote the unknown true values of the parameters of the technical inefficiency model.

The SFP model with a flexible risk specification includes mean output function, risk function and technical inefficiency which are estimated simultaneously using the maximum likelihood method by using Stata software (Version 15).

Statement of Hypothesis:

The following hypotheses were tested to determine the ability of the model to achieve the study objectives and whether input production risk and technical inefficiency can significantly explain production variations. The hypotheses are listed below:

1- H_0: α_{ij} =0, the coefficients of the second-order variables in the Translog model are zero in favor of the Cobb-Douglas model.

2- H_0: $\beta_1=\ldots=\beta_{14}=0$, output variability is not explained by production risk in inputs and socio-economic variables.

3- H_0: $\lambda=0$, inefficiency effects are absent from the model. Therefore, the variance of the inefficiency term is zero and deviations of the observed output from the frontier output are entirely due to pure noise effect. On the other hand, if $\lambda>0$ then technical inefficiency is present in the data and deviations from the frontier output are as a result of technical inefficiency and pure noise.

4- H_0: $\gamma_1=\ldots=\gamma_{20}=0$, this implies that inputs and socio-economic variables do not account for technical inefficiency. The generalized likelihood-ratio statistic (LR test) tested the entire hypothesis. The statistic for this test is as follows:

$$LR = -2[lnL_r - lnL_{ur}] \sim \chi^2 \qquad (14)$$

In Equation 14, L_r is the value of the likelihood function of the restricted model, and L_{ur} is the value of the likelihood function of the unrestricted model. The likelihood ratio (LR) test statistic has a χ^2 distribution with degrees of freedom equal to the number of parameters under the null hypothesis.

Data and Sampling Technique

The statistical population in this study consisted of rice farmers in Rasht County. Based on data from the Agricultural Jihad Organization of Guilan province (2016), the total number of farmers at the time of the study was 38,763. Using Cochran's formula with a margin of error of 0.065, the required sample size was calculated to be 226, representing approximately 58 percent of the population. Although more questionnaires were distributed and completed, only 221 were deemed usable for analysis.

The questionnaire consisted of two parts. The first part was related to the inputs used in the rice production process, and the second part was related to the socio-economic variables of farmers and their farms. It should be noted that Stata and Excel software were used to analyze the data.

A descriptive analysis of variables is presented in Table 1; subsequently the demographic characteristics of the respondents were expressed.

Table 1- Summary statistics of output and input variables

Variable	Symbol	Type of variable	Unit	Mean	Min	Max	SD
Production	pro	Dependent	Ton	4.94	0.2	36	4.96
Land	ln	Independent	Hectare	1.33	0.112	10	1.24
Seed	se	Independent	Kilogram	98.92	12	450	77.54
Labour	la	Independent	Man-days	29.50	3	128	20.82
Nitrate fertilizer	n	Independent	Kilogram	258.35	0	3500	344.37
Phosphate fertilizer	p	Independent	Kilogram	142.28	0	4000	294.74
Herbicide	hs	Independent	Liter	4.51	0	35	4.51
Machinery	ma	Independent	Hour	65.68	4	795	77.60

Source: Research Findings

According to Table 1, the average cultivated area was 1.33 hectares. On average, rice farmers used 98.92 kilograms of rice seed, 29.50 man-days of labor, 258.35 kilograms of nitrogen fertilizer, 142.28 kilograms of phosphate fertilizer, 4.51 liters of pesticide, and 65.68 hours of agricultural machinery to produce 4.94 tons of output. Based on the completed questionnaires, the average age of rice farmers was 51 years, with over 97% being married. The average household size was three members, and 92% of the farmers were male. Rice farming was the primary occupation for more than 53% of respondents, and over 81%

were landowners. Regarding machinery ownership, only 10% of farmers owned machinery, while the remainder relied on rental equipment. Additionally, more than 48% of farms were insured, and 21% of farmers had participated in educational programs.

Table 2- Results of estimation of the stochastic frontier model and efficiency with and without risk consideration

		Model estimation with risk component			Model estimation without risk component		
variable definition	**Symbol**	**Coefficients**	**z**	**P>|z|**	**Coefficients**	**z**	**P>|z|**
Production function							
Constant	cons	0.01	0.58	0.56	-0.042	-1.11	0.266
Log Land	lln	1.11***	22.02	0.000	0.756***	6.98	0.000
Log Seed	lse	-0.125**	-2.45	0.014	-0.049	-0.65	0.514
Log Labour	lla	0.05*	1.95	0.051	0.027	0.5	0.62
Log Nitrate fertilizer	ln	-0.004	-0.14	0.888	0.167***	2.8	0.005
Log Phosphate fertilizer	lp	0.008	0.29	0.775	0.128**	2.48	0.013
Log Herbicide	lhs	0.019	0.47	0.642	0.045	0.7	0.482
Log Machinery	lma	-0.002	-0.07	0.947	-0.016	-0.29	0.771
0.5*(Log Land)^2	lln^2	1.377***	19.92	0.000	0.789***	5.71	0.000
0.5*(Log Seed)^2	lse^2	0.643***	3.85	0.000	0.202	0.77	0.44
0.5*(Log Labour)^2	lla^2	-0.283***	-2.58	0.01	0.066	0.51	0.607
0.5*(Log Nitrate)^2	ln^2	0.059***	2.63	0.009	0.05**	2.14	0.033
0.5*(Log Phosphate)^2	lp^2	0.003	0.66	0.507	0.024***	2.66	0.008
0.5*(Log Herbicide)^2	lhs	0.048	1.08	0.278	0.006	0.23	0.816
0.5*(Log Machinery)^2	lma^2	0.053	0.58	0.565	0.103	0.94	0.349
Log Land*Log Seed	llnlse	-1.087***	-8.79	0.000	-0.225	-0.88	0.376
Log Land*Log Labour	llnlla	0.773***	9.77	0.000	0.305**	2.41	0.016
Log Land*Log Nitrate	llnln	-0.272***	-3.57	0.000	-0.17*	-1.79	0.074
Log Land*Log Phosphate	llnlp	-0.011*	-1.92	0.055	-0.012	-1.02	0.307
Log Land*Log Herbicide	llnlhs	-0.232***	-5.5	0.000	-0.041	-0.45	0.65
Log Land*Log Machinery	llnlma	-0.022	-0.26	0.797	-0.414***	-2.94	0.003
Log Seed*Log Labour	lsella	-0.122	-1.45	0.148	-0.259*	-1.79	0.073
Log Seed*Log Nitrate	lseln	-0.599	-1.35	0.178	-0.021	-0.31	0.755
Log Seed*Log Phosphate	lselp	-0.013	-0.57	0.568	-0.013	-0.3	0.763
Log Seed*Log Herbicide	lselhs	0.442***	5.85	0.000	0.004	0.04	0.968
Log Seed*Log Machinery	lselma	0.065	0.98	0.328	0.262**	2.26	0.024
Log Labour*Log Nitrate	llaln	0.055	0.73	0.463	-0.053	-0.54	0.588
Log Labour*Log Phosphate	llalp	0.069***	5.08	0.000	0.062**	2.44	0.014
Log Labour*Log Herbicide	llalhs	-0.198**	-2.09	0.037	0.088	1.13	0.26
Log Labour*Log Machinery	llalma	-0.27***	-3.66	0.000	-0.165*	-1.77	0.076
Log Nitrate*Log Phosphate	lnlp	-0.028**	-2.46	0.014	-0.007	-0.54	0.588
Log Nitrate*Log Herbicide	lnlhs	0.032	1.12	0.261	0.041	1.06	0.287
Log Nitrate*Log Machinery	lnlma	0.12***	2.77	0.006	0.094	1.44	0.15
Log Phosphate*Log Herbicide	lplhs	-0.037	-1.25	0.213	-0.55	-1.37	0.171
Log Phosphate*Log Machinery	lplma	-0.007	-0.4	0.687	-0.009	-0.47	0.639
Log Herbicide *Log Machinery	lhslma	-0.093**	-2.48	0.013	0.011	0.14	0.888
Risk function							
Constant	Cons	-9.187***	-5.18	0.000	-	-	-
Land	ln	4.409***	7.84	0.000	-	-	-
Seed	se	-0.045***	-5.53	0.000	-	-	-
Labour	la	-0.005	-0.58	0.562	-	-	-
Nitrate fertilizer	n	-0.001	-1.23	0.22	-	-	-
Phosphate fertilizer	p	-0.0007	-0.44	0.662	-	-	-
Herbicide	hs	-0.342***	-3.77	0.000	-	-	-
Machinery	ma	-0.006**	-2.05	0.04	-	-	-
Water	wa	1.458**	2.38	0.017	-	-	-
Age	age	0.128***	6.23	0.000	-	-	-
Gender	gen	3.877***	3.05	0.002	-	-	-
Marital status	marr	-0.819	-0.85	0.397	-	-	-
Educational level	edu	-0.249*	-1.95	0.051	-	-	-
Household size	famsize	-0.556***	-5.45	0.000	-	-	-
Experience	exper	-0.076***	-4.62	0.000	-	-	-

Technical inefficiency function							
Constant	cons	-1.6	-0.43	0.669	-13.74*	-1.77	0.076
Land	ln	-1.213	-0.84	0.401	10.91	1.1	0.269
Seed	se	0.037***	2.69	0.007	-0.002	-0.15	0.882
Labour	la	0.058*	1.73	0.083	0.034	0.54	0.59
Nitrate fertilizer	n	-0.034***	-4.1	0.000	-0.017	-1.12	0.261
Phosphate fertilizer	p	0.005	0.62	0.535	0.017	1.29	0.196
Herbicide	hs	0.357	1.08	0.279	-2.115	-1.24	0.215
Machinery	ma	0.005	0.76	0.446	-0.058	-1.32	0.188
Water	wa	-2.486***	-2.63	0.008	-7.97**	-2.05	0.04
Age	age	-0.039	-0.63	0.530	0.225	0.86	0.388
Gender	gen	-2.761***	-2.73	0.006	4.91	0.99	0.321
Marital status	marr	2.397	0.92	0.355	-11.93	-0.89	0.374
Educational level	edu	0.039	0.13	0.895	-1.884	-0.43	0.669
Household size	famsize	0.221	0.79	0.432	1.487	1.12	0.263
Experience	exper	-0.118**	-2.05	0.041	-0.44	-0.91	0.365
Main occupation	otherjob	0.339	0.37	0.713	5.167**	1.98	0.048
Land ownership	pland	0.407	0.35	0.726	6.261	0.96	0.338
Machinery ownership	pmachine	0.837	0.63	0.529	6.534	0.88	0.38
Membership in cooperatives	membershipe	3.081***	3.82	0.000	6.598**	2.18	0.029
Insurance	insure	2.682***	3.57	0.000	4.656	1.05	0.295
Participating in training classes	class	-10.66***	-3.56	0.000	-2.463	-0.95	0.342
Observations		221			221		
Log likelihood		55.07			-10.5368		
Wald chi2(35)		422720.45			1973.21		
Prob>chi2		0.000			0.000		
E(sigma-u)		0.1581			-		
E(sigma-v)		0.2919			-		
lambda ($\lambda = \frac{\sigma_u}{\sigma_v}$)		0.54			-		

Source: Research Findings ***, **, * indicate 0.01, 0.05 and 0.1 level of significance respectively.

Results and Discussion

Estimated Generalized SFP Model

The results of estimating the stochastic frontier function with and without considering risk are reported in Table 2. Since Translog coefficients cannot be directly interpreted, input elasticities were calculated for economic interpretation.

Results of Estimated Production Elasticity and Returns to Scale (RTS)

The concept of input elasticity in a production function is used to determine the stage of production in which the rice farmers are operating in using each input. The output elasticity shows the degree of responsiveness of rice output to changes in the amount of various inputs and a summation of the partial elasticities of the various inputs with respect to output is a measure of the return to scale of the rice farms.

Table 3- Estimation results of production elasticities and returns to scale

Variable	Elasticities	Production Area
Land	1.04	First
Seed	-0.251	Third
Labour	-0.046	Third
Nitrate fertilizer	0.258	Second
Phosphate fertilizer	0.033	Second
Herbicide	0.058	Second
Machinery	0.0003	Second
Returns to Scale (RTS)	1.092	-

Source: Research Findings

According to Table 3, the elasticity of land input is positive and equals 1.04, showing one percent increase in the use of land input will increase output by 1.04 percent, and this input was used in the first stage of production in the studied area. The elasticities of nitrate and phosphate fertilizers, herbicide and machinery inputs had a positive sign and were 0.258, 0.033, 0.058 and 0.0003, respectively. It means that a one percent increase in the usage of nitrate and phosphate fertilizers, herbicide and machinery inputs will increase output by 0.258, 0.033, 0.058 and 0.0003 percent, respectively. Also, the value of these elasticities is between zero and one, indicating that farmers were currently operating in the second stage of production for these inputs. Consistent with our findings, Esfandiari *et al.*, (2013) similarly reported positive production elasticities for both land and phosphate fertilizer inputs in rice production of Marvdasht County, Fars province.

The seed input exhibited a negative elasticity of 0.251 percent, indicating that one percent increase in seed usage would decrease mean production by 0.251 percent. This negative elasticity value suggests over-utilization of seeds in the study area. In production economic terms, this places seed usage in Stage III of the production function (the irrational zone of production).

The labour input demonstrated negative elasticity (-0.046 percent), implying that a one percent increase in labour usage would reduce mean output by 0.046 percent. This statistically significant negative elasticity confirms that labour is being overutilized in the study area, placing it in Stage III of the production function - the economically inefficient zone where the marginal product is negative.

The sum of the partial elasticities of inputs to output indicates returns to scale (RTS) and, in fact, the flexibility of production.

The returns to scale coefficient was estimated at 1.092. This means that a one percent increase in the use of production inputs increases the amount of rice produced by more than one percent, which is called increasing returns to scale. Sharzehei *et al.*, (2001) also found that rice production in Guilan province exhibits increasing returns to scale.

Production Risk Function

Output variability in the production process has been explained by the inputs and exogenous variables which provide important information for production risk management. According to the estimated coefficients of the production risk function in the middle part of Table 2, the inputs of area under cultivation (Land), water, farmer's age, and gender increase production risk, and seeds, herbicides, machinery, education, household size, and rice farming experience reduce production risk.

In other words, the land input coefficient was obtained as 4.409, showing that land input has a significant and positive effect on the risk of rice production and is a risk-increasing input. Because rice farming is labor-intensive, increasing the area under cultivation makes it difficult for each farmer to control the farm, and the time spent per square meter during the planting and harvesting stages of the rice crop decreases. This result is consistent with the findings of Yazdani & Sassuli (2008), Kopahi *et al.* (2009), Esfandiari *et al.* (2013), Villano & Fleming (2006), Tiedemann & Latacz-Lohmann (2013), Guttormsen & Roll (2014) and Oppong *et al.* (2016).

The coefficient of water inputs was also 1.458, which indicates that water has a positive and significant effect on rice production risk. Because of the abundant rainfall and climate conditions of the studied area, water input is considered as a dummy variable, usage of water from channels against traditional sources of water supply. Because the channels' water is released on a certain date, it leads to a delay in the preparation of rice paddy fields and defers the stages of the rice production process, which increases production costs. So water is a risk-increasing input, which is consistent with Yazdani & Sassuli (2008) on investigating the effects of inputs on the risk of rice production.

The coefficient for seed input was -0.045, indicating that seed has a negative and statistically significant effect on rice production risk. This suggests that seed is a risk-reducing input. Risk-averse farmers tend to use more seed to reduce output variability. In the study area, rice farmers were observed to use higher quantities of seed, primarily for two reasons: (1) after transplanting, some seedlings were displaced or damaged by water flow; and (2) in some cases, seedling stems were severed and destroyed by aquatic insects, necessitating replacement with healthy seedlings. Farmers used the seedlings remaining in the storage to reduce the production risk. The studies of Guttormsen & Roll (2014), Baawuah (2015) and Oppong *et al*. (2016) confirm this finding. The herbicide input coefficient was also found to be -0.342. It means that herbicide had a significant and negative effect on rice production risk. Using herbicide to destroy weeds can create sturdy rice bushes and improve the quality and quantity of the product. Similarly, Kopahi *et al*. (2009), Villano *et al*. (2005), Villano & Fleming (2006) and Baawuah (2015) found that herbicide is risk reducing input in rice production. The input of machinery became significant, with a coefficient of -0.006. This means that machinery was a risk-reducing input. This implies that proper management of machinery can be used to reduce output variance. This result is in agreement with the findings of Karbasi *et al*. (2005), Adinku (2013), and Hosseinzad & Alefi (2016).

Studies investigating the impact of inputs on production risk (Yazdani & Sassoli, 2008; Karbasi et al., 2005; Sharzehei & Zibaei, 2001) have shown that only a small portion of production risk is attributable to input use. Instead, various other factors significantly influence production risk, including the farm's geographical location, the farmer’s age, level of education or experience, gender, access to credit, availability of extension services, rainfall patterns, and the type of agricultural soil. Therefore, in the present study, in addition to examining the effect of inputs on production risk, the effect of factors such as the farmer's age, education level, experience, and farmer's gender, marital status, and household size on production risk was examined. These results are explained below.

According to Table 3, the coefficient of the age variable was 0.128 and was significant. It means that age is a risk-increasing variable. As farmers get older their physical and cognitive powers diminish and the one behaves more conservatively and risk-averse showing a less tendency to adopt new technologies. Also, older farmers are more likely to be at individual risk. The coefficient of the gender variable was 3.877 and had a significant positive effect on production risk. If the manager and decision maker of a farm is male, he will take more risky decisions. This can be consistent with the general belief that women are relatively risk-averse. On the other hand, men have more financial independence than women, which can affect their decision-making. It can be true, especially in rural communities where women are more responsible for household duties. This result is consistent with the studies of Wik *et al*. (2004) and Guttormsen & Roll (2014). The coefficient of the education variable in the production risk function was -0.249. This variable had a negative and significant effect on production variance and it was a risk-reducing factor. The higher level of education will reduce the production risk cause more educated farmers have comprehensive vision and a better understanding of issues related to their profession including production, markets for selling their product. The coefficient of the household size variable was -0.556 and was statistically significant. This result shows that the household size variable has a negative and significant effect on the risk of rice production and is a risk-reducing variable. A big family is considered to have more labour input at different stages of production, reducing the risk of labour scarcity in the production process and so on the production risk. The coefficient of the agricultural experience variable was -0.076 and was statistically significant. So, the experience of farmers in producing rice reduces production risk and is a risk reducing variable. The experienced farmers work better in their field of agricultural activities, which can ultimately improve productivity and reduce production risk.

Labour, nitrate and phosphate fertilizers, and marital status did not have a significant effect on the risk of rice production in the studied area. The labour has a negative sign and is a risk decreasing input, but not significant in this study. The studies of Yazdani & Sassuli (2008), Kopahi *et al.* (2009), Ogundari & Akinbogun (2010), Alikhani *et al.* (2015), Baawuah (2015) and Hosseinzad & Alefi (2016) also confirmed that labour is a risk reducing input.

Technical Inefficiency Model

The last part of Table 2 shows the results of estimating the technical inefficiency function. It should be noted that negative signs of the estimated variables indicate positive effects on technical efficiency, which imply such variables reduce rice production inefficiency, and the positive sign shows the negative effect on technical efficiency. According to Table 2, the seed variable coefficient was obtained as 0.037. It means that with each additional unit of seed used, the amount of 0.037 units of farm inefficiency increases. So, seed has a positive and significant effect on technical inefficiency, indicating that farmers who have used more seeds were less efficient. Using more seed increases production costs and on the other hand, by increasing output density per hectare land reduces marginal productivity.

The coefficient of labour input was 0.058 and was statistically significant. This indicates that labour input has a positive effect on the technical inefficiency of rice farms. Using more labour due to the high level of wages increases production costs, and on the other hand, because of the excessive labour accumulation per hectare, production decreases. The coefficient of the variable membership in cooperatives was also positive and significant, with a value of 3.081. This means that membership in cooperatives in the study area had a positive effect on the technical inefficiency of farmers. Cooperative companies have different categories according to their activities. The cooperative corporations distribute various types of fertilizers and herbicides. Some cooperatives in the studied area were inactive, and rice farmers had to buy these inputs from the market at higher prices, which in turn would increase production costs. It should be mentioned that active cooperatives recommended fertilizers and herbicides to farmers without any soil testing and just based on their own experience, which cannot be the optimum amounts. According to the studies of Esfandiari *et al.* (2013) and Alikhani *et al.* (2015), membership in cooperatives has a significant relationship with technical inefficiency, which can be positive or negative. According to the results, the crop insurance variable also became significant, with a coefficient of 2.682 and had a positive effect on the technical inefficiency of rice farmers. Most of the rice farmers who had insured their product did not receive any indemnity after damage or received only a little, which was not enough to cover their costs. Thus, they considered the rice insurance program as an additional useless cost that only increases their production costs. Also, a large number of rice farmers had small farms, and due to the high amount of premium, they did not insure their product. The coefficient of nitrate fertilizer was -0.034. This means that nitrate fertilizer had a negative and significant effect on the technical inefficiency of rice farmers. In other words, nitrate fertilizer has a positive effect on technical efficiency and increases it. Nitrate fertilizer is an important input for increasing rice yield and can increase production if used at the right time. Water input had a negative and significant effect on the inefficiency of rice farmers. In other words, water input has a positive effect on the technical efficiency of farmers. The coefficient of water input was calculated as -2.486. As mentioned earlier, this input was considered a dummy variable. Using the water of channel because of the stability of its source increases technical efficiency. The findings of Esfandiari *et al.* (2013) also showed that the source of water supply has a positive effect on technical efficiency in rice production.

In this study, the gender variable was significant with a coefficient of -2.761. So, Men work more efficiently than women. This could be explained by the fact that men have easier access to credit, probably because of cultural prejudice, and hence men are closer to the production frontier. Also, men are more interested in expanding their activities. This result is consistent with the findings of Kibaara (2005), Onumah & Acquah (2010), Taraka *et al*. (2012), Adinku (2013), Baawuah (2015) and Kea *et al*. (2016). The experience variable with a coefficient of -0.118 had a negative and significant effect on farmers' inefficiency. In other words, experienced farmers are less inefficient. So, there is a positive relationship between farmers' experience and technical efficiency. Findings of Esfandiari *et al*. (2013), and Alikhani *et al*. (2015), Ogundari & Akinbogun (2010), and Taraka *et al*. (2012) also confirm this result. Educational classes was also significant with a value of -10.66. This variable had a negative effect on technical inefficiency and in other words a positive effect on the technical efficiency of rice farmers in the studied region. Educational classes that upgrade farmers' information and their managerial capacity, will increase production efficiency. Phosphate fertilizer, herbicide, machinery, age, marital status, education, household size, non-agricultural occupation, land ownership, and machinery ownership did not affect the technical inefficiency of rice farmers in the studied area. Adinku (2013) showed that age, land ownership, size of household and main occupation did not have any significant effect on technical inefficiency of rice production in Ghana. Also, according to Esfandiari *et al*. (2013), the variables of household size, primary occupation, and machinery ownership did not affect the technical efficiency of rice production in Iran.

Testing of Hypotheses

The likelihood ratio test (LR) results for the hypothesizes of the study are presented in Table 4.

Table 4- Hypothesis test for model specification and statistical assumptions of stochastic frontier model with flexible risk properties

Null Hypothesis	Log-likelihood Value	LR Test	Critical value (α=0.001)	Decision
1. H_0: $\alpha_{ij} = 0$	-27.18	164.52***	58.30	Reject H_0
2. H_0: $\beta_1=\ldots=\beta_{14}=0$	-10.53	131.23***	36.12	Reject H_0
3. H_0: $\lambda=0$	-42.68	195.5***	67.98	Reject H_0
4. H_0: $\gamma_1=\ldots=\gamma_{20}=0$	22.63	64.89***	48.26	Reject H_0

Source: Research Findings *** statistically significante at 0.001 significance level.

According to the Table 4:

1- The Translog model is an adequate representation of the data, given its specification.

2- Production risk in inputs and socio-economic variables and technical inefficiency are present and estimated lambda is 0.54 and it is significantly greater than zero. This implies that variations in the observed output from the frontier output is due to technical inefficiency (u) and random noise (v).

4- The study finds technical inefficiencies are explained by the exogenous factors and the conventional input factors.

Comparison of Technical Efficiency Values with Risk and without Risk Component

The results of estimating technical efficiency with and without considering risk components are shown in Table 5.

Table 5- Technical efficiency with and without risk component

Technical efficiency	Min	Max	SD	Mean	Technical inefficiency
Technical efficiency with risk	25.37	100	12.31	93.47	6.53
Technical efficiency without risk component	15.49	100	10.43	96.27	3.73

Source: Research findings

The average technical efficiency of farms with the risk component was 93.47 percent. In this case, there is a 6.53 percent inefficiency (Table 5). Also, the average technical efficiency of farms without considering risk was 96.27 percent. That is, in this case, the units have a

3.73 percent inefficiency.

Therefore, considering risk in the production process clearly affects technical efficiency. The difference in the efficiency in both cases indicates that with the same amounts of inputs and facilities, the production level can be increased significantly, and this increase in production increases when the factors that create risk can be controlled. Therefore, it can be concluded that by considering risk in production, production can be increased by 6.53 percent by using available resources efficiently. Without considering risk, this amount reaches 3.73 percent. The economic interpretation of the efficiency estimate can be expressed as follows: On average, rice farmers in the study area can increase their technical efficiency by 6.53 percent (with risk component) and 3.73 percent (without risk component) without requiring additional resources for production. So, the technical efficiency score is overestimated when the production risk component is excluded. So, the conventional stochastic frontier model understimates technical efficiency scores than a stochastic frontier model with flexible risk specification. This result is consistent with findings of Alikhani *et al.* (2015), Ogundari & Akinbogun (2010), Adinku (2013), Baawuah (2015) and Oppong *et al.* (2016).

Conclusion and Recommendation

This study was carried out to investigate the technical efficiency and production risk of rice paddy fields in Rasht County, Iran, using the stochastic frontier model with flexible risk properties. In this model, the Translog production function was estimated simultaneously with production risk and technical inefficiency by a single-stage maximum likelihood estimation. The Translog production function was the most appropriate functional form for the production function part in the generalized SFP model of Kumbhakar (2002). Since the coefficients in the Translog function are not interpreted directly, the concept of input elasticity should be used for interpretation. The results showed that (i) the elasticity of cultivated area, nitrogen fertilizer, phosphorus fertilizer, herbicide, and machinery were positive, increasing these inputs could potentially increase the average production; (ii) the production elasticity of seed and labour was negative, indicating that higher levels of these inputs—relative to the study sample—led to a decrease in average rice production. (iii) the rice fields studied in Rasht exhibited increasing returns to scale. Moreover, variations in production were found to be influenced by input-related production risk. According to the estimated coefficients of the production risk function, certain inputs—including cultivated area, water usage, farmer's age, and gender—were identified as risk-increasing factors. In contrast, inputs such as seed, herbicide, machinery, farmer education, household size, and rice farming experience were found to reduce production risk, indicating their role as risk-reducing inputs.

Changes in technical efficiency are explained by the combination of the effects of inputs and exogenous variables. The results of the estimation of the technical inefficiency model showed that seed inputs, labor, membership in cooperatives, and agricultural insurance had a positive and significant effect on the technical inefficiency of rice production units in the study area, and the variables of nitrogen fertilizer, water, gender, rice cultivation experience, and participation in educational and extension programs had a negative and significant effect on the inefficiency of the units. Based on the results, farms in the study area operate below the production frontier, and this deviation from the production frontier was due to technical inefficiency and risk.

The average technical efficiency estimated using the stochastic frontier function with flexible risk properties was 93.47%, and the average technical efficiency calculated without considering the risk component was 96.27%, which showed a higher value. Therefore, it is observed that not considering the risk component in estimating technical efficiency leads to biased results of technical efficiency. Based on the findings of this study, the following recommendations are made to help farmers and policymakers to increase rice output, eliminating technical inefficiencies and decreasing the effect of risk in the production process by knowledge transfer through organizing practical training and encouraging farmers participation in cooperatives corporations to improve farmers knowledge on optimized usage of seed, cultivation area, nitrogen fertilizer, herbicides, and machinery. Additionally, facilitating farmers access to financial support, i.e. loan, to upgrade machineries can improve farmers efficiency. Finally, given the impact of agricultural insurance (specifically rice insurance), it is recommended that insurers fulfill their obligations by providing full and prompt compensation for damages, in order to encourage rice farmers to adopt this risk management tool

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مقاله پژوهشی

جلد ۳۹، شماره ۲، تابستان ۱۴۰۴، ص. ۱۸۰-۱۶۵

ارزیابی همزمان کارایی فنی و ریسک تولید مزارع برنج

هانیه کظمی شعبانزاده افلاکی [۱]- عذرا جوان‌بخت [۱*]- خدیجه الفی [۲]

تاریخ دریافت: ۱۴۰۳/۱۰/۲۴
تاریخ پذیرش: ۱۴۰۴/۰۱/۲۷

چکیده

فعالیت‌های کشاورزی در مقایسه با سایر فعالیت‌های تولیدی، فعالیتی پرریسک بوده و این ریسک اغلب با ناکارآمدی همراه است. بنابراین مطالعه همزمان ریسک و عدم کارایی می‌تواند منجر به تولید کاراتر شود. بر اساس داده‌های سازمان جهاد کشاورزی استان گیلان (سال ۱۳۹۵)، تعداد کل کشاورزان در زمان مطالعه ۳۸۷۶۳ نفر بود. با استفاده از فرمول کوکران، حجم نمونه مورد نیاز ۲۲۶ نفر محاسبه شد که تقریباً ۵۸ درصد از جمعیت را تشکیل می‌دهد. پرسشنامه شامل دو بخش بود که به‌ترتیب مربوط به نهاده‌های مورد استفاده در فرآیند تولید برنج و متغیرهای اجتماعی-اقتصادی کشاورزان و مزارع آنها بود. برای ارزیابی همزمان کارایی فنی و ریسک تولید برنج‌کاران، در شهرستان رشت در سال ۱۳۹۷، از یک مدل تولید مرزی تصادفی تعمیم‌یافته (SFP) با ویژگی‌های ریسک انعطاف‌پذیر استفاده شد. نتایج تخمین تابع ریسک تولید نشان داد که تولید برنج به‌طور معنی‌داری تحت تأثیر نهاده‌های زمین، بذر و نیروی کار قرار دارد. همچنین، نهاده‌های سطح زیرکشت، آب، سن شالیکار و جنسیت ریسک فزاینده و بذر، علف‌کش‌ها، ماشین‌آلات، تحصیلات کشاورز، اندازه خانواده و تجربه کشاورزی از نهاده‌های ریسک کاهنده هستند. علاوه بر این، بذر، نیروی کار، عضویت در تعاونی‌های کشاورزی و بیمه، ناکارایی فنی را افزایش می‌دهد. کود نیترات، آب، جنسیت، تجربه کشت برنج و شرکت در کلاس‌های آموزشی و ترویجی اثر مثبت بر کارایی فنی در منطقه‌ی مورد مطالعه داشتند. نتایج برآورد کارایی فنی نشان داد که میانگین کارایی فنی شالیکاران با مؤلفه ریسک ۹۳/۴۷ درصد و بدون مؤلفه ریسک ۹۶/۲۷ درصد بوده است. بنابراین واضح است که برآورد مدل بدون مؤلفه ریسک منجر به خطای بزرگنمایی در میزان کارایی فنی می‌شود. در نتیجه، توصیه می‌شود هنگام اندازه‌گیری کارایی فنی شالیزارها برای دستیابی به مدیریت ریسک صحیح و تولید بسیار کارآمد، مؤلفه ریسک در نظر گرفته شود.

واژه‌های کلیدی: ریسک تولید، شالیکاری، کارایی فنی، مدل مرزی تصادفی (SPF)، مدیریت ریسک، نهاده‌های کشاورزی

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https://doi.org/10.22067/jead.2025.91636.1327

Journal of Agricultural Economics & Development

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

Research Article
Vol. 39, No. 2, Summer 2025, p. 181-192

Determining the Optimal Cropping Pattern with Emphasis on the Interaction between Risk and Profitability: Farmlands of Dehgolan Plain

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Received: 08-11-2024 Revised: 17-12-2024 Accepted: 31-12-2024 Available Online: 31-12-2024	**How to cite this article:** Ghasabi, M., Haji-Rahimi, M., Ghaderzadeh, H., & Shankayi, R. (2025). Determining the optimal cropping pattern with emphasis on the interaction between risk and profitability: Farmlands of Dehgolan plain. *Journal of Agricultural Economics & Development, 39*(2), 181-192. https://doi.org/10.22067/jead.2024.90686.1312

Abstract

Risk is an undeniable factor in agricultural activities, and its neglect can lead to inefficient resource allocation in the sector. Various theories and mathematical programming models have been developed to assist decision-making in cropping pattern management under risk conditions. This study aimed to determine the optimal cropping pattern for Dehgolan Plain, Iran, using data from 2014 to 2023. A linear programming model was employed to maximize farmers' gross income, and the results were compared with those from a Quadratic Programming Model and the Minimization of Total Absolute Deviation (MOTAD) model, both incorporating risk minimization. The findings revealed that risk factors can significantly influence cropping patterns. Under the highest level of risk, the profit-maximizing cropping pattern included only cucumber, alfalfa, and canola, indicating a preference for higher gross-income crops despite their greater water requirements. However, when risk was incorporated into the model, the cultivated area of wheat and barley increased compared to the risk-neutral scenario. This shift reflects a tendency toward lower water-requirement crops, even at the cost of reduced gross income. These results highlight the necessity of balancing income maximization and risk management for more sustainable cropping pattern.

Keywords: Cropping pattern, Linear programming model, MOTAD model, Quadratic programming model, Risk model

Introduction

Agriculture is one of the most vital sectors of the global economy (Gebbers & Adamchuk, 2010) which requires a comprehensive planning to achieve growth and address ongoing crises (Zhou *et al.*, 2022). Agricultural activities have long been characterized by high levels of risk and uncertainty, stemming from the sector's constant exposure to a wide range of unpredictable biophysical, economic, and institutional factors (Theuvsen, 2013). Unlike many other industries, agriculture is uniquely vulnerable to weather variability, pests and diseases, volatile market prices, and shifting policy frameworks, all of which can lead to substantial fluctuations in yields and incomes. This financial and operational uncertainty is not incidental but rather a defining feature of agricultural production systems (Adnan *et al.*, 2018). The cumulative effect of these risks extends beyond individual farms, posing

https://doi.org/10.22067/jead.2024.90686.1312

serious challenges to food security, rural development, and the overall resilience of agricultural economies.

Agricultural risk is multidimensional, encompassing various factors that influence farm operations, productivity, and profitability. According to Ozerova and Sharopatova (2021), six primary sources of risk in agriculture (production, price, financial, institutional, technological, and personal) play a crucial role in shaping decision-making and outcomes in farming systems (Fig. 1). Identifying and addressing these diverse sources of risk is crucial for developing comprehensive risk management frameworks that enhance the stability and productivity of agricultural systems.

Farmers are often compelled to make decisions regarding resource allocation and crop production in environments where risks related to prices and crop yields prevail. The numerous risks inherent in the agricultural sector can significantly influence cropping patterns and the composition of cultivated crops (Wang *et al.*, 2022). The intrinsic nature of risk entails adverse outcomes such as reduced returns and income, which, in severe cases, may lead to crises like financial bankruptcy, food insecurity, and health-related challenges (Komarek *et al.*, 2020).

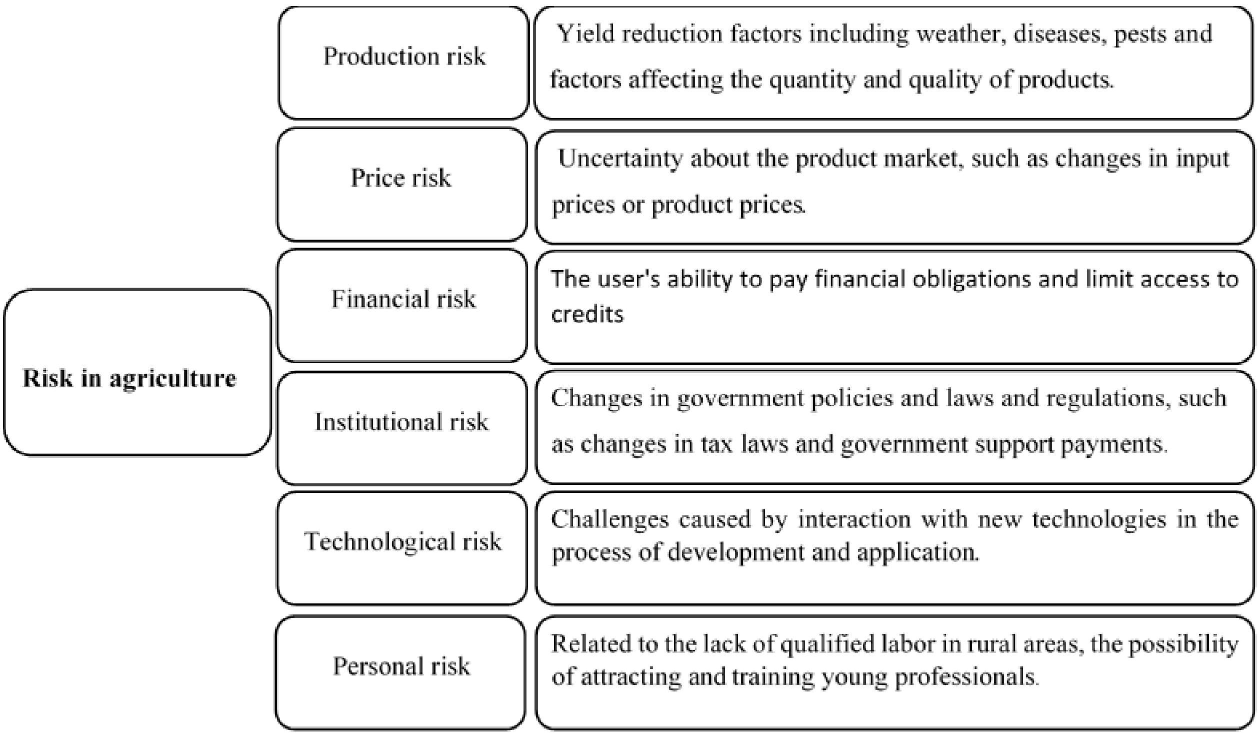


Figure 1- Classification of sources of risk in the agricultural sector

Simple mathematical programming methods, due to their inability to account for risk, often fail to provide farmers with optimal production plans. Faced with production risks and price volatility of future crops, farmers exhibit varying behaviors. Therefore, to better predict optimal cropping patterns, it is crucial to incorporate risk factors into the decision-making process for agricultural activities (Ahmad *et al.*, 2020). Consequently, to achieve agricultural development, it seems logical to integrate risk considerations into planning, policymaking, and decisions regarding optimal crop composition and cultivation levels (Bahadori *et al.*, 2019).

Although Iran's economic growth is not heavily reliant on agricultural production, agriculture plays a crucial role in the economy due to its significant contributions to employment, food security, non-oil exports, and foreign exchange earnings (Deylami & Joolaie, 2023). Additionally, the persistence of poverty in Iran has consistently influenced macro-level decision-making related to the agricultural sector. On the one hand, most workers in the agricultural sector are low-income rural residents, and on the other hand, agriculture provides food security for those working in this sector and others (Mousavi & Esmaeili, 2011). Therefore, agriculture holds a strategic role in ensuring food security for the country's growing population (Tahami Pour Zarandi *et al*., 2019). It is essential for farmers and policymakers to mitigate the adverse effects of common risks and optimize the utilization of the country's productive resources. Studies on risk programming models have analyzed farmers' decision-making processes and the impacts of risks, presenting optimal cropping patterns under varying levels of risk and comparing the results with linear programming models. A review of previous studies indicates that, while international research on risk models is more extensive, domestic studies in this field remain relatively limited.

The linear programming (LP) model is a mathematical method used to optimize a linear objective function—typically maximizing profit or minimizing cost—subject to a set of linear constraints representing resource limitations such as land, labor, water, or capital. Due to its clarity, computational efficiency, and versatility, LP has become one of the most widely adopted tools in agricultural planning and farm management (Singh *et al*., 2001). In the context of agriculture, LP models are especially useful for determining optimal cropping patterns by identifying the most efficient allocation of limited resources to maximize returns under assumed certainty.

However, one major limitation of conventional LP is its inability to incorporate risk and uncertainty, which are inherent features of agricultural production due to factors such as weather variability, market price fluctuations, pest outbreaks, and changing policy environments. To address this shortcoming, Hazell (1971) introduced the Minimization of Total Absolute Deviation (MOTAD) model, a risk programming approach that builds upon LP by incorporating income variability as a risk component. The MOTAD model retains the linear structure and computational advantages of LP while enabling risk-averse decision-making by minimizing the mean absolute deviation of income from its expected value. Unlike quadratic programming approaches—which can be mathematically complex and computationally demanding—MOTAD remains linear, making it suitable for practical application in large-scale farm models and regional agricultural planning. This feature has led to its widespread use in risk-sensitive agricultural decision-making, particularly in developing countries where farmers face substantial production and market uncertainties. By integrating both LP and MOTAD models, researchers and planners can compare risk-neutral and risk-aware scenarios, offering more comprehensive guidance for optimal farm planning that balances profitability with resilience.

Yu *et al*. (2022) used the MOTAD model to optimize input allocation for risk-exposed farming households in northern China, demonstrating that diversification significantly improves both risk management and productivity. Pyman (2021), using a quadratic programming model, found that while crop diversification in Malawi can reduce production and price risks, it may come at the cost of lower overall farm returns. Magreta *et al*. (2021) applied the Target MOTAD method to analyze smallholder maize farming in Malawi, revealing that farmers mitigate climatic risks through resource reallocation and crop diversification strategies. Negm and Abdullah (2021) evaluated cropping pattern risks using linear and nonlinear models, with MOTAD results showing that the risk-adjusted net return model outperformed the alternative by increasing net returns by 6.7%, optimizing water use, expanding cultivated areas, and enhancing self-sufficiency in strategic. Lu *et al*. (2020), using panel data and the MOTAD model, found that climate change—especially temperature shifts—significantly reduced crop yields in China, potentially decreasing cultivated area by 6%, and recommended a 15% reduction in total cultivated land with reallocation toward strategic crops for effective adaptation. Bahadori *et al.* (2019) optimized cropping patterns in Rey County using linear programming and multiple MOTAD-based risk models, revealing that while current resource use was inefficient, incorporating risk into the models showed a positive correlation between risk exposure and returns. Similarly, Bahadori and Hosseini (2018) used linear programming, quadratic programming, and MOTAD to determine optimal cropping patterns, finding that risk-based optimization led to increased cultivation of rainfed rice, wheat, and canola. However, under high-risk scenarios, the results aligned closely with those of linear programming. Both risk models confirmed a direct positive relationship between farm risk and program returns. A review of previous studies shows that most research on optimal cropping patterns has utilized deterministic programming models.

This study aims to evaluate the impact of production risk on the selection of optimal cropping patterns for irrigated crops in the Dehgolan Plain, using both linear programming and risk-based programming models.

Materials and Methods

The study focuses on the Dehgolan plain, located in the Kurdistan province of Iran. This region is characterized by its agricultural significance, with irrigated cropping systems being the primary source of livelihood for local farmers. The plain's climate and soil conditions make it an ideal case study for examining the impacts of risk on agricultural decision-making, particularly in terms of selecting optimal cropping patterns under various risk scenarios. Nevertheless, Dehgolan plain is one of the fertile regions of Kurdistan province, Iran, but it experiences inconsistent rainfall distribution and evaporation exceeding annual precipitation. This semi-humid, cold region is among the drier areas of Kurdistan, leading to significant variability in crop yields (Ghasabi *et al.*, 2024). Selecting a cropping pattern that minimizes the adverse effects of these fluctuations is essential.

To determine the optimal cropping pattern, this study employs linear programming (LP) and risk-based models including the MOTAD and Target MOTAD models. The primary objective is to maximize farm profitability while accounting for the uncertainties inherent in agricultural production. LP model can be demonstrated as below:

$$Max \quad Z = \sum_{(J=1)}^{n} C_j X_j \qquad (1)$$

S.t:

$$\sum_{(J=1)}^{n} a_{ij} X_j \le b_j \qquad j = 1, 2, 3, \ldots, m \qquad (2)$$

$$X_j \ge 0 \qquad j = 1, 2, 3, \ldots, n \qquad (3)$$

In equation 1, Z represents the objective function, which maximizes the total gross income, C_j is the coefficient of the objective function (the predicted gross income for one unit of the jth farming activity), and X_j is the decision variable (the area allocated to the jth farming activity). Equation 2 expresses the resource availability or technical constraints a_{ij} are the technical coefficients (the amount of resource i used by one unit of activity j), b_i is the available quantity of resource i, and m represents the number of limiting resources. In this study, the technical constraints include agricultural land, water resources, labor, chemical fertilizers, pesticides, markets, and machinery. Equation 3 shows the non-negativity constraints of the variables, and n represents the number of activities.

On the other hand, quadratic programming is based on the idea that the utility function can be expressed in terms of the expected value (E) and variance (V). In this model, risk is estimated through the variance of income from various events (equation 4).

$$V = \sum_j \sum_k X_j X_k \sigma_{jk} \qquad (4)$$

X_j and X_k represent the levels of the jth and kth farm activities, respectively, while σ_{jk} denotes the variance-covariance matrix of the gross income between the jth and kth activities. When j=k, σ_{jk} represents the variance.

Hazell proposed the use of variance estimates based on the Mean Absolute Deviation (MAD) of the sample. If sample data and classical methods are used to estimate variances and covariances, the variance of income in the quadratic programming model is calculated as shown in equation 5 (Norton & Hazell, 1986):

$$\hat{V} = \sum_j \sum_k X_j X_k \left[(1/T-1) \sum_{(T=1)}^{t} [C_{jt} - \bar{C}_j][C_{kt} - \bar{C}_k] \right] \quad (5)$$

In this equation, t=1…T, T represents the sample observations, and C_{jt} is the gross income of the jth activity in the tth year, with the sample mean of gross income denoted by $\bar{C}_j$.

By summing over t and factoring, the estimated variance will be expressed as equation (6). (Norton & Hazell, 1986):

$$\hat{V} = (1/T-1) \sum_t \left[\sum_j C_{jt} X_j - \sum_j \bar{C}_{jt} X_j \right]^2 = (1/T-1) \sum_t [Y_t - \bar{y}]^2 \quad (6)$$

That is, the variance of farm income for a specific production plan can be expressed as an aggregated form of variances and covariances of each activity, or more simply, by calculating the farm income (Y_t) corresponding to each observation of the gross income of activities and estimating the variance of a single random variable. This transformation enables the use of the MAD estimator for the variance of Y. The MAD estimator is given by (Norton & Hazell, 1986):

In this equation, the term in brackets represents the sample MAD, and F is a fixed coefficient that relates the sample MAD to the population variance. Specifically, the relationship is given by $\mathrm{F} = \frac{\mathrm{T}\pi}{2(\mathrm{T}-1)}$, where π is a mathematical constant (Norton & Hazell, 1986).

An important point regarding the MAD estimator is that if, in a quadratic programming model, the above relationship is substituted in the objective function instead of minimizing variance, the result can be a linear programming model.

The deviation of farm income from its mean in year t is represented as Z_t^+ if it is positive, and Z_t^- if it is negative (equation 7):

$$\sum_t (Z_t^+ + Z_t^-) = \sum_j C_{jt} X_j - \sum_j \bar{C}_j X_j \quad (7)$$

This equation measures the total absolute deviation in income for a given farm plan. Accordingly, the MAD estimator of variance is expressed as equation 8:

$$\hat{V} = F \left\{ \left(\frac{1}{T} \right) \sum_j [Z_t^+ + Z_t^-] \right\}^2 \quad (8)$$

Since $\frac{F}{T^2}$ is a constant for a given farm plan, it can be divided by $\hat{V}$ to yield the equation 9:

$$W = (\frac{T^2}{F})\hat{V} = \left\{ \sum_t \left[Z_t^+ + Z_t^- \right] \right\}^2 \quad (9)$$

Moreover, since the ranking of farm plans is based on $w^{\frac{1}{2}}$, to rank the plans based on W, the square root of W can be calculated. In that case, the linear programming model formulated in equations 10 to 14 can be considered as a substitute for the quadratic programming model:

$$Min \quad W^{\frac{1}{2}} = \sum_{t=1}^{T} (Z_t^+ + Z_t^-) \quad (10)$$

S.t:

$$\sum_{j=1}^{n} (C_{jt} - \bar{C}_j) X_j - Z_t^+ + Z_t^- = 0 \qquad \forall t \quad (11)$$

$$\sum_{j=1}^{n} \bar{C}_j X_j = E \quad (12)$$

$$\sum_{j=1}^{n} a_{ij} X_j \le b_i \qquad \forall i \quad (13)$$

$$X_j, Z_t^+, Z_t^- \ge 0 \qquad \forall j,t \quad (14)$$

This above model can be solved using parametric linear programming to obtain the E-V efficient set of farm plans.

Since the total negative deviations of income from the mean $\sum_t Z_t^-$ must always equal the total positive deviations $\sum_t Z_t^+$, it is sufficient to minimize one of these sums and multiply the result by two to obtain $W^{\frac{1}{2}}$. Here, the negative deviations are chosen, and the compact

MOTAD model, considering the negative deviations, can be written as equation 15 to 19:

$$Min \quad 0.5W^{\frac{1}{2}} = \sum_{t=1}^{T} Z_t^- \tag{15}$$

$$\sum_{j=1}^{n} (C_{jt} - \bar{C}_j) X_j - Z_t^+ + Z_t^- = 0 \qquad \forall t \tag{16}$$

$$\sum_{j=1}^{n} \bar{C}_j X_j = E \tag{17}$$

$$\sum_{j=1}^{n} a_{ij} X_j \le b_i \qquad \forall i \tag{18}$$

$$X_j, Z_t^- \ge 0 \tag{19}$$

The data used in this study were collected through in-person visits to the Kurdistan Regional Water Company, the Kurdistan Agricultural Jihad Organization, and the National Water Demand System for six major crops grown in the Dehgolan Plain, including wheat, barley, potato, cucumber, alfalfa, and canola, over the agricultural years 2014 to 2023. These six selected crops account for more than 85% of the total cultivated area in the study area. It should be noted that Microsoft Excel Solver was used to estimate the models employed in this research.

Results and Discussion

Results of the Linear Programming Model

The total cultivated area for all crops in the studied plain is approximately 19,000 hectares. Wheat, with an area of 7,000 hectares (over 36% of the total), occupies the largest share of the cultivated land. The main factors driving the expansion of wheat cultivation in this region include government support (due to guaranteed purchase prices), lower water requirements, and resistance to adverse climatic conditions. Fig. 2 shows the average gross income, cultivated area, yield, and water consumption for the major crops in the Dehgolan plain. In the absence of resource constraints, the optimal solution of the model would lead to the sole production of cucumber, as each kilogram of cucumber generates a higher income.

The results of conventional linear programming model for studied area are presented in Table 1. According to the table, wheat and alfalfa hold the largest shares in the current cropping pattern. However, in the optimal pattern derived from linear programming (LP), crops with higher gross income per hectare are recommended, subject to the existing constraints.

The optimal cropping pattern for maximizing gross income in the Dehgolan plain prioritizes cucumber, alfalfa, and canola, while excluding wheat, barley, and potato due to their lower economic returns. Despite wheat and barley's lower water requirements and guaranteed market through government pricing, their reduced cultivation is economically justified but challenging for farmers to accept. The optimal scenario highlights an increase in cucumber and canola cultivation, with cucumber reaching its maximum production level, emphasizing its role in gross income enhancement. Conversely, potato cultivation is significantly reduced.

Table 1- The cultivated area of each product in the current and the optimal crop pattern of LP

Product	Current status (ha)	Optimum status (ha)	Amount of changes (ha)
Wheat	7000	0	-7000
Barley	1100	0	-1100
Cucumber	710	9493.82	8784
Potato	4260	0	-4260
Alfalfa	5400	5122.63	-277
Canola	518	4371.56	3854
Gross income (million Tomans)	753231.82	1764400.83	1011169.01

Source: Research Results

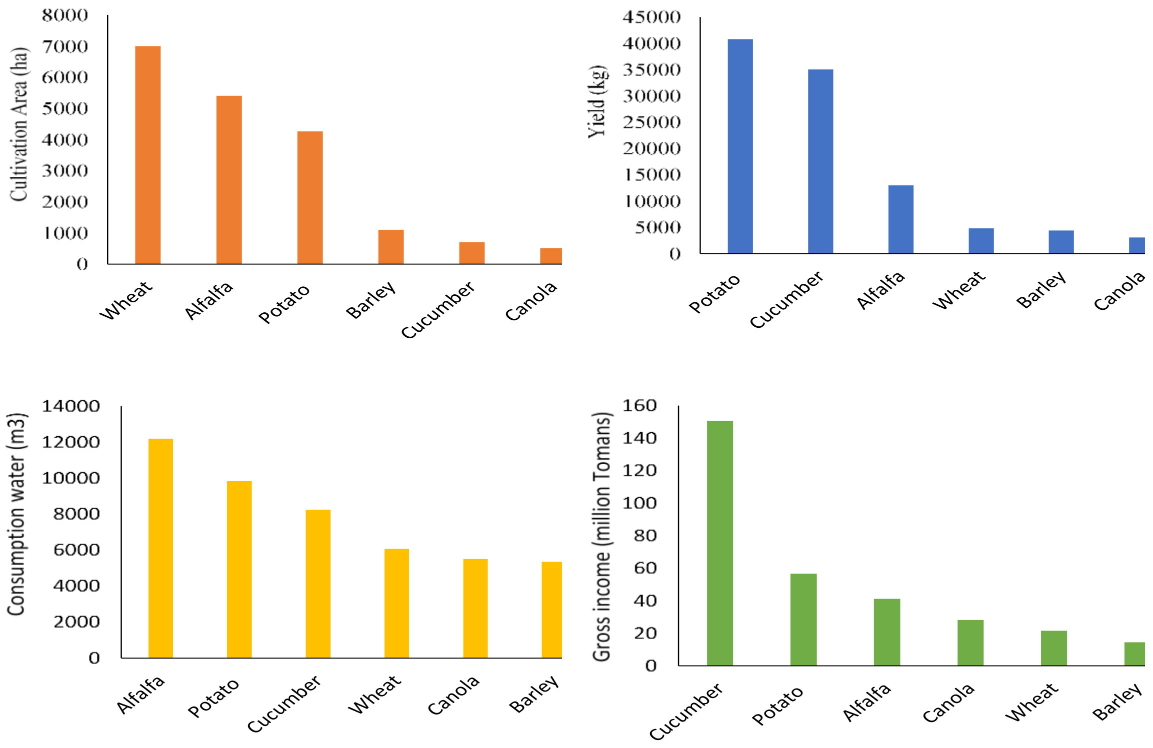


Figure 2- Cultivated area, yield, water use and gross income of each agricultural product

Maximizing gross income incorporates water-intensive crops with high returns, though this approach conflicts with the region's severe water scarcity. Expanding alfalfa cultivation is notable, offering both direct economic benefits and indirect advantages as a critical livestock feed, particularly given its rising market value. However, alfalfa's high-water demand poses challenges in a water-restricted plain.

The comparison between current and optimal patterns reveals inefficiencies in resource use, suggesting that income could be substantially improved under the optimal model. However, such patterns entail higher risks, making them better suited for risk-tolerant farmers. Ultimately, balancing economic gains with sustainable water resource management remains critical in this water-scarce region.

Risk Programming Models

To examine the effect of risk on the optimal cropping pattern, the income risk, which is influenced by two important parameters—price fluctuations and income fluctuations—was assessed. To achieve this objective, the variance-covariance matrix was first estimated, and then the objective function of a quadratic programming model was constructed to minimize the variance of gross income across activities. Technical constraints were incorporated into the model, which was then evaluated by varying the expected income parameter. Since the expected income level can be arbitrarily defined in the quadratic risk programming model, this study presents the optimal cropping patterns corresponding to eight different levels of expected income, as shown in Table 2. The results indicate that the cropping pattern responds to changes in the level of risk.

Table 2- The results of the Quadratic Programming Model

Plan	Expected income	Risk	Wheat	Barley	Cucumber	Potato	Alfalfa	Canola
1	1764401	1570263	0	0	9493.81	0	5122.63	4371.56
2	1760000	1517491	0	0	9493.81	0	5109.10	4366.61
3	1750000	1441616	0	0	9237.01	256.81	4939.54	4264.68
4	1740000	1311871	255.66	0	9176.72	317.09	4769.98	4058.77
5	1730000	1180683	527.15	0	9139.72	354.10	4600.42	4011.14
6	1720000	1050808	1098.64	0	9102.71	391.10	4430.86	3964.68
7	1710000	914203	1610.14	0	9065.71	428.11	4365.28	3500.30
8	1700000	777073	1861.63	100	9028.70	465.11	4141.42	3391.14

Source: Research Results

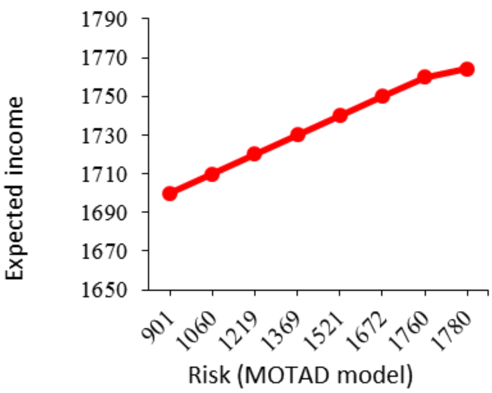
*Expected income and risk in millions of Tomans (10 Rials) and cultivated area of crops in hectares.

The first plan in Table 2 corresponds to the risk-neutral solution or the maximization of income, which is the preferred pattern for a farmer who aims to maximize income without considering risk. In fact, the results of plan 1 at the highest risk level are the same as those obtained from linear programming.

Moving from plan 1 to plan 8, the expected income decreases, and so does the risk level. The area under wheat cultivation increases as risk decreases. Given that wheat is the raw material for bread and one of the country's strategic crops, its production has always been a priority for agricultural policymakers. The government has implemented guaranteed purchase policies to support farmers and stabilize their incomes. The increase in guaranteed prices and the implementation of wheat-centered policies have reduced the production risk of this crop. Therefore, actions must be taken to ensure food security for the growing population. The area under cucumber, alfalfa and canola cultivation in the linear programming model has decreased compared to the current situation.

Comparison of MOTAD and Quadratic Programming Models

The comparison of the optimal values derived from the MOTAD model and the Quadratic Programming model indicates that both approaches exhibit similar behavioral patterns. Fig. 3 presents the efficient frontier, depicting the relationship between income and risk. The chart clearly demonstrates that as the level of risk increases, the expected income rises correspondingly, eventually attaining the maximum achievable income as determined by linear programming solutions. This observed relationship underscores the inherent trade-off between income and risk within these modeling frameworks, providing valuable insights into the decision-making process under uncertainty. By quantifying this trade-off, both models offer robust tools for optimizing resource allocation while considering varying levels of risk tolerance.



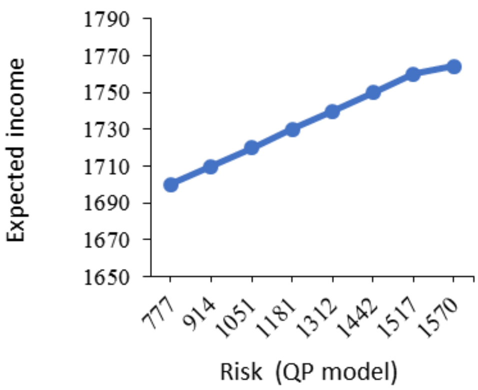


Figure 3- The efficient frontier of expected income and risk (billion Tomans)

At the risk level of 1,780,133 million Tomans, the highest risk level, the cropping pattern only includes cucumber, alfalfa, and canola, which have higher gross income, and with a decrease in expected income and reaching a risk level of 1,060,285 million Tomans, the area allocated to these crops decreases. In other words, as expected income increases, the cropping pattern shifts toward replacing products with higher gross income. The results from the MOTAD model also confirm that with a reduction in risk, crops such as wheat, barley, and potatoes become more attractive to farmers. Therefore, when a farmer seeks a more secure behavior and reduces risk, they must accept lower incomes.

The risk estimated by the MOTAD model is higher than that of the quadratic programming model. This discrepancy arises because the mean absolute deviation estimation used in the MOTAD model is less precise compared to the traditional nonlinear estimation employed in quadratic programming. A key advantage of the MOTAD model, however, is its compatibility with linear programming (LP) solvers. This feature allows for the inclusion of more detailed production and marketing strategies when formulating the model.

Conclusion

This study aimed to develop an optimal cropping pattern for the Dehgolan plain, Iran, under both risk-free and risk-based scenarios. The results from the risk-free scenario revealed inefficiencies in the current cropping pattern. Since price fluctuations of products and inputs (price risk) and yield variability (yield risk) contribute to income volatility, this study employed income variability as a risk indicator.

A key finding is that risk-based models demonstrate a direct relationship between risk and gross income. For crops like wheat, barley, and potatoes, incorporating risk into the model increases the cultivated area of wheat compared to linear programming outcomes, aligning with governmental strategic objectives and national food security goals. At lower income levels, potatoes emerge as a preferred choice among horticultural crops due to favorable market conditions.

Non-strategic crops such as cucumbers, which face limited governmental intervention in cultivation and market development, yield significantly higher gross income. This profitability offsets the higher risks associated with these crops. Additionally, the low cost of water in the Dehgolan plain compared to its shadow price (Ghasabi *et al*., 2024) results in a larger share of water-intensive crops in the optimal pattern. To address water scarcity, the study recommends shifting irrigated wheat cultivation to rainfed practices and implementing effective water storage techniques to enhance spring crop yields and mitigate warm-season water shortages.

While government interventions reduce production risks, they distort crop selection. A reduced governmental role in agricultural production and a reevaluation of policies are recommended. Farmers should prioritize cultivating low-risk crops to secure stable income under uncertain conditions. Multi-cropping systems and crop rotation are effective strategies to mitigate risk and reduce income fluctuations, addressing crop-specific pests, diseases, and price volatility. Government policies should focus on maximizing farmers' income while ensuring stability and sustainability in production.

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مقاله پژوهشی

جلد ۳۹، شماره ۲، تابستان ۱۴۰۴، ص. ۱۹۲-۱۸۱

تعیین الگوی بهینه کشت با تأکید بر تعامل ریسک و سودآوری: اراضی کشاورزی دشت دهگلان

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تاریخ دریافت: ۱۴۰۳/۰۸/۱۸
تاریخ پذیرش: ۱۴۰۳/۱۰/۱۱

چکیده

ریسک یکی از عوامل مهم در فعالیت‌های کشاورزی است و نادیده گرفتن آن می‌تواند به تخصیص ناکارآمد منابع در این بخش منجر شود. نظریه‌ها و مدل‌های مختلف برنامه‌ریزی ریاضی برای کمک به تصمیم‌گیری در مدیریت الگوی کشت در شرایط ریسکی توسعه یافته‌اند. هدف این مطالعه تعیین الگوی بهینه کشت در دشت دهگلان با استفاده از داده‌های دوره زمانی ۱۳۹۳ تا ۱۴۰۲ بود. در این راستا، از مدل برنامه‌ریزی خطی برای حداکثرسازی درآمد ناخالص کشاورزان استفاده شد و نتایج آن با مدل برنامه‌ریزی درجه دوم و مدل حداقل‌سازی انحراف مطلق کل (MOTAD) که هر دو به کاهش ریسک توجه دارند، مقایسه گردید. یافته‌ها نشان داد که عامل ریسک می‌تواند به‌طور معناداری الگوی کشت را تغییر دهد؛ در بالاترین سطح ریسک، الگوی کشتِ مبتنی بر حداکثرسازی سود با استفاده ار برنامه‌ریزی خطی ساده تنها شامل خیار، یونجه و کلزا بود که بیانگر ترجیح محصولات با درآمد ناخالص بالاتر، علی‌رغم نیاز بیشتر به منابع آبی، است. در شرایط در نظر گرفتن ریسک در مدل‌های برنامه‌ریزی ریسکی، سطح زیر کشت گندم و جو نسبت به حالت بدون در نظر گرفتن ریسک افزایش یافت که نشان‌دهنده گرایش به سوی محصولات با نیاز آبی کمتر باوجود کاهش درآمد ناخالص است. این نتایج بر ضرورت برقراری توازن میان حداکثرسازی درآمد و مدیریت ریسک به‌منظور دستیابی به الگوی کشت پایدارتر تأکید دارد.

واژه‌های کلیدی: الگوی کشت، مدل ریسک، مدل برنامه‌ریزی خطی، مدل برنامه‌ریزی درجه دوم، مدل MOTAD

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https://doi.org/10.22067/jead.2024.90686.1312

Journal of Agricultural Economics & Development

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

Research Article
Vol. 39, No. 2, Summer 2025, p. 193-210

Analyzing Food Consumption Patterns in Rural Areas of Iran: Identifying Provinces with Standard and Homogeneous Consumption

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Received: 09-02-2025 Revised: 09-04-2025 Accepted: 26-04-2025 Available Online: 26-04-2025	**How to cite this article:** Shabanzadeh-Khoshrody, M. (2025). Analyzing food consumption patterns in rural areas of Iran: Identifying provinces with standard and homogeneous consumption. *Journal of Agricultural Economics & Development, 39*(2), 193-210. https://doi.org/10.22067/jead.2025.92120.1333

Abstract

Investigating food consumption patterns in rural areas of Iran is necessary to understand the state of food security and social health in the country. Identifying provinces with standard and homogeneous consumption patterns not only helps improve planning to meet food needs, but also can lead to the formulation of appropriate and effective policies to address issues related to nutrition and public health. This study examined: (i) the current food consumption patterns in rural areas of Iran in 2023, compared to the standard dietary pattern; (ii) the ranking of provinces based on the similarity of their dietary patterns to the standard; (iii) the identification of similar food consumption patterns across rural regions in different provinces; and (iv) the relationship between food consumption patterns and the infrastructural, economic, and social indicators of the provinces. The methodology of this study includes statistical analysis tools, such as TOPSIS method and k-means clustering technique. The results showed that the current dietary pattern of households in rural areas of Iran mainly consists of various types of cereals, providing more than 60% of an adult's daily calorie intake. Comparing, global scale, cereals provide 50% of daily calories intake, averagely, varying from 30% to 55% and 70% in high, middle, and low-income societies, respectively. We found that food consumption in rural areas of Iran does not necessarily align with the standard pattern, meaning 28.4% lower food items than required in the standard basket, and 16% less than standard energy requirements. For instance, the consumption of bread was more than recommended level while the share of dairy products, fruits, and red meat, was 64.4%, 52.1%, and 50% lower than the recommended amount, respectively. While the dietary patterns in rural areas of six provinces - Chaharmahal and Bakhtiari, Markazi, Isfahan, Hamedan, Zanjan, and Mazandaran - satisfied the standard dietary. The converse evidence was observed for Hormozgan, Semnan, Kerman, North Khorasan, Ilam, and Sistan-Baluchestan. Between comparison of provinces confirmed (i) a heterogenous consumption pattern, mostly, dominated by five types of behavioral patterns; (ii) non-significant effect between consumption pattern and geographical distribution; (iii) a more desirable consumption pattern depending on more suitable infrastructure, economic, and social indicators. To deal with the undesirable consequences of calorie shortage and non-standard consumption pattern, this study suggests a comprehensive plan regulating supportive policies, public awareness, sustainable agriculture, and educational programs about nutrition and market access. Nutrition in rural regions is influenced by economic, regional, social, cultural, and individual factors, and improving dietary health necessitates addressing these interconnected elements.

Keywords: Calorie intake, Dietary preferences, k-means clustering, Rural households, Standard food basket, TOPSIS method

https://doi.org/10.22067/jead.2025.92120.1333

Introduction

Nutrition is closely related to health, and the type, quantity, and quality of food that people consume daily have a profound impact on their health status. Variety in dietary patterns is essential for providing the necessary micronutrients in sufficient quantities. A healthy diet can help reduce the risk of nutrition-related diseases and prevent illness and infection by supplying essential nutrients. To maintain the health of family members, it is recommended to consume 20 to 30 different types of food throughout the week (Wen *et al*., 2024). According to World Bank statistics, the world population is estimated to reach 2.8 billion in 2024. Of this amount, about 43 percent, or more than 3.5 billion people, live in rural areas. Given that a large portion of the population, especially in developing countries, resides in rural areas, improving and promoting their nutritional status and food security is a crucial goal (Sheibani *et al*., 2020).

The concept of food security is especially crucial in rural areas, as these areas play a significant role in food production. Rural areas are known as the main centers of agricultural production but often face the issue of poverty. Poverty rates among rural residents are nearly three times higher than urban residents, and over 80 percent of people living in extreme poverty reside in these areas (UNICEF, 2024). This situation can result in reduced access to food, malnutrition, and other health problems in rural communities. A healthy workforce possesses the physical and mental capabilities necessary to work effectively, ultimately increasing productivity. However, poor nutrition can lead to a decrease in the productivity of farmers in rural areas (Siddique *et al*., 2020). In 2019, 94.7 million deaths worldwide were attributed to poor diet, with a significant portion linked to low food intake in rural regions. Additionally, in low- and middle-income countries, a considerable number of smallholder farmers are at risk of malnutrition (Nandi *et al*., 2021). Given that the agricultural production process is generally labor-intensive, it is crucial to prioritize the health, diversity, and food security of households in rural areas to ensure the sustainability of production and meet growing demand (Weil *et al*., 2023).

It is often assumed that farmers in rural areas can improve their families' dietary diversity by growing a variety of crops and diversifying their farm produce. However, the relationship between farm product diversity and dietary diversity has not been conclusively confirmed in empirical studies (Snapp & Fisher, 2015; Hirvonen & Hoddinott, 2017; Sibhatu & Qaim, 2018; Zanello *et al*., 2019). While it is generally believed that growing different crops and raising livestock in smallholder households can provide essential micronutrients, there is limited empirical evidence on how agricultural production impacts the nutrition of farming families. This is because most smallholders sell their own produce and purchase food items from local markets. Furthermore, many researchers argue that productivity growth in the agricultural sector, particularly for smallholders, has not significantly improved the diversity and food security of farming families. Productivity improvements have mainly focused on staple crops like rice, wheat, and corn, which only offer a limited amount of essential vitamins and minerals. Food and nutritional security are influenced by food diversity, not just food quantity, and therefore, having access to healthy, diverse, and affordable food is crucial for household food security (Webb & Kennedy, 2014; Ruel *et al*., 2017; Usman & Callo-Concha, 2021).

Rural areas in Iran, with a population of over 24 million out of 83 million people, play a vital role in the country's social, economic, and cultural structure (Statistical Center of Iran, 2024). Traditionally, these areas have had their own unique patterns in terms of access to food resources, dietary habits, and local cultures. However, with the influence of economic and social changes, dietary habits in these areas have also significantly changed (Forouhesh & Soltani, 2024). Various studies have been conducted on food consumption in rural areas of Iran. These studies can be broadly divided into three groups. The first group of studies has examined food consumption patterns. Literature have extensively contributed to food consumption patterns (e.g., Bakshoodeh, 2005; Rostami *et al*., 2016; Amjadi & Barikani, 2020; Sheibani & Karbasi, 2020; Forouhesh & Soltani, 2024). The second group of studies has focused on factors influencing consumption, diversity, and food security (e.g., Shirani Bidabadi & Ahmadi Kaliji, 2013; Jamini *et al*., 2017; Charaghi *et al*., 2018; Okati *et al*., 2020; Sheibani *et al*., 2020; Ghaderi, 2024; Galedarvand *et al*., 2024), Also Sharify (2020) and Shabanzadeh-Khoshrody *et al.* (2023) investigated the impact of government policies on consumption and food security.

A review of the history of studies reveals that there have been few studies conducted on food consumption patterns in rural areas of Iran. Most studies either focus on the past or cover the entire country or a specific province's rural areas. Furthermore, these studies did not analyze provinces with standard dietary patterns or those with similar consumption habits and explore the relationship between food consumption patterns and the economic, social, and climatic capacities of rural areas in different provinces. Understanding the nutritional status and content of the household consumption basket in various provinces and comparing it with the standard situation is crucial for governments. This information can serve as a valuable guide for future planning. Identifying provinces with homogeneous and standardized consumption patterns can help in developing strategies tailored to local needs and conditions.

Various variables affect the dietary diversity of households in rural areas, and the nutritional status of each individual depends on several factors, including physical, physiological, cultural, technological, economic, religious, and environmental factors (Ludwig, 2018). According to a study by Adelaja *et al.* (1997), economic factors, including household income, are important and determining factors in household nutritional patterns. Variyam's (2003) suggests that demographic variables such as household size, age, and race play a significant role in household consumption patterns. Streeter (2017) and Lourenção *et al.* (2021) have shown that cultural and economic variables are determinants of household consumption. In the studies by Facina *et al.* (2023) and Weil *et al.* (2023), the role of economic and social variables in determining household consumption patterns has been emphasized.

This article first analyzes the current pattern of food consumption in rural areas of Iran and compares this pattern with the standard pattern. Next, it identifies and ranks the provinces whose dietary patterns are closest to the standard pattern. Then, it identifies provinces with similar food consumption patterns and draws a map of food consumption patterns in rural areas of Iran. Finally, it examines the relationship between food consumption patterns and the infrastructural, economic, and social indicators of the provinces[1].

Materials and Methods

The research methodology of the present study consists of four main parts including (i) the method used to identify the current food consumption pattern in rural areas of Iran; (ii) the method used to identify provinces with a food pattern close to the standard food pattern within the framework of the TOPSIS method; (iii) how the k-means clustering method was used to identify provinces with similar food consumption patterns, and (iv) the method used to examine the relationship between food consumption patterns and the infrastructural, economic, and social indicators of the provinces.

Identifying Household Consumption Patterns

[1]- The provinces of Iran are characterized by a significant amount of ethnic, religious, linguistic, and cultural diversity. Since the cost-income design relies heavily on statistical samples, the chosen samples may not accurately reflect the various ethnicities and religions present. These differences, which pertain to cost and income data, are outside the researchers' control and could potentially impact the results, introducing bias to some extent.

To calculate the index for rural areas of Iran in 2023, we first used cost-income data from the Statistical Center of Iran to construct a nutritional performance matrix. This matrix is created by multiplying two matrices: one containing consumption amounts of items and the other containing calories received per hundred grams of food. The first matrix's rows represent household food items, while its columns show the amounts consumed by rural households. The second matrix's rows show calories, and its columns indicate nutrients obtained from food items per hundred grams. Information on nutrients from various items was sourced from the Iranian Institute of Nutrition and Food Industries. The nutritional performance matrix for rural households is determined by multiplying the aforementioned matrices. Under the assumption of a linear function, the calorie content model equation can be expressed as equation (1) (Smed *et al*., 2005; Akerele, 2011; Shabanzadeh-Khoshrody & Hosseini, 2021).

$$y_h^* = \sum_{j=1}^{n=k} \beta_j X_{hj} + \varepsilon_h \qquad (1)$$

Where, y_h^* represents the calorie intake level of the h^{th} household member, X_{hj} is the amount of the j^{th} food item consumed by the h^{th} household member, and β_j is the energy content of the j^{th} food item. It is worth noting that energy content coefficients have been calculated based on various geographical zones and climates. By dividing the matrix by the average number of household members, and, subsequently, by 30, we calculated the monthly and daily calorie per capita, respectively. Then, we followed the procedure of Adult Male Equivalents (AMEs) of calorie (Shabanzadeh-Khoshrody *et al*., 2024) to unify calorie intake across household members.

This procedure was repeated for all ten diet components, including bread and grains, red meat and poultry, fish and seafood, milk, cheese and eggs oils and fats fruits and nuts, vegetables and cereals, sugar and sweets, non-alcoholic beverages, and other food types.

TOPSIS Method

In the present study, the TOPSIS method was utilized to rank and identify provinces with food consumption patterns that align closely with the diet recommended by the Ministry of Health and Medical Education of I.R. Iran. The primary rationale for employing this method in the study was the presence of both negative and positive indicators used for comparison and ranking. Specifically, as some provinces in the country have food consumption levels above the standard while others fall below, the TOPSIS method allows for foods with higher consumption levels to be viewed as negative factors and those with lower consumption levels as positive factors for ranking purposes. The TOPSIS method for ranking is predicated on the idea that the chosen option should have the shortest distance to the positive ideal solution and the longest distance from the negative ideal solution. In this method, a total of 31 provinces were evaluated based on the average daily per capita consumption of various food items including bread, rice, Macaroni, legumes, potatoes, vegetables, fruits, red meat, poultry, eggs, dairy products, vegetable oils, and sugar. Each evaluation can be visualized as a geometric system consisting of *m* points in an *n*-dimensional space. The TOPSIS method involves seven steps, as outlined below.

Step 1: The initial step in the TOPSIS method is to create a decision matrix. This matrix will consist of *m* options and *n* indicators. The overall structure of the matrix is as follows:

In the matrix above, A_i represents the i^{th} option and X_{ij} represents the numerical value obtained from the i^{th} option with the j^{th} index. The profit index includes the average daily per capita consumption of rice, Macaroni, legumes, potatoes, vegetables, fruits, red meat, poultry, eggs, and dairy products. The loss index includes the average daily per capita consumption of bread, vegetable oils, and sugar.

$$D = \begin{array}{c} \\ A1 \\ A2 \\ \cdot \\ \cdot \\ \cdot \\ Ai \\ \cdot \\ \cdot \\ \cdot \\ Am \end{array} \begin{array}{c} \begin{array}{cccccccccc} X1 & X2 & \cdot & \cdot & \cdot & Xj & \cdot & \cdot & \cdot & Xn \end{array} \\ \begin{bmatrix} X11 & X12 & \cdot & \cdot & \cdot & X1j & \cdot & \cdot & \cdot & X1n \\ X21 & X22 & \cdot & \cdot & \cdot & X2j & \cdot & \cdot & \cdot & X2n \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ Xi1 & Xi2 & \cdot & \cdot & \cdot & Xij & \cdot & \cdot & \cdot & Xin \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ Xm1 & Xm2 & \cdot & \cdot & \cdot & Xmj & \cdot & \cdot & \cdot & Xmn \end{bmatrix} \end{array} \qquad (2)$$

Step 2: In this step, the decision matrix is normalized. The scales in the decision matrix are converted to dimensionless scales, where each value is divided by the size of the component corresponding to the same index. This division results in obtaining each element r_{ij} from equation (3).

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^{2}}} \qquad (3)$$

Step 3: The third step in the TOPSIS method involves weighting the normalized matrix. The decision matrix is defined parametrically, so it must be quantified. To do this, the decision maker assigns a weight to each indicator. These weights (*w*) are then multiplied by the normalized matrix (*R*). It is important to note that the sum of the weights assigned to the indicators must equal one. In this study, different weights were assigned to the goods based on their share in the standard basket of goods proposed by the Ministry of Health (Table 2).

$$W = (w_1, w_2, \dots, w_j, \dots, w_n) \qquad \sum_{j=1}^{n} w_j = 1 \qquad (4)$$

Before multiplying the normalized decision matrix (*n*×*n*) by the *Wn*×*1* matrix, the weight matrix must first be converted into a *Wn*×*n* diagonal matrix, with the weights placed on the main diagonal.

Step 4: In this step, we determine the positive ideal solution (A^{+}) and the negative ideal solution (A^{-}). To do this, we define two virtual options, A^{+} and A^{-}, as shown in equation (5):

$$\begin{aligned} A^{+} &= \{(\max v_{ij} \mid j \in J), (\min v_{ij} \mid j \in \acute{J}) \mid i = 1,2,\dots,m\} = \{v_1^{+}, v_2^{+}, \dots, v_j^{+}, \dots, v_n^{+}\} \\ A^{-} &= \{(\min v_{ij} \mid j \in J), (\max v_{ij} \mid j \in \acute{J}) \mid i = 1,2,\dots,m\} = \{v_1^{-}, v_2^{-}, \dots, v_j^{-}, \dots, v_n^{-}\} \\ J &= \{j = 1,2,3,\dots,n\} \\ \acute{J} &= \{j = 1,2,3,\dots,n\} \end{aligned} \qquad (5)$$

The two virtual options actually represent the worst and best solutions.

Step 5: The fifth step in the TOPSIS method is to calculate the distances. In this step, the distance of each *n*-dimensional option is measured using the Euclidean method. In other words, the distance of option *i* from the positive and negative ideal options is calculated using equations (6) and (7).

$$S_{i+} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{+})^2}, \quad i = 1,2,3,\dots,m \qquad (6)$$

$$S_{i-} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{-})^2}, \quad i = 1,2,3,\dots,m \qquad (7)$$

Step 6: In this step, we calculate the relative proximity of each option to the ideal solution. The TOPSIS method utilizes equation (8) to determine the relative proximity to the ideal solution.

$$C_{i*} = \frac{S_{i-}}{S_{i+} + S_{i-}}, \quad 0 < C_{i*} < 1 \qquad (8)$$

In the given relationship, if $A_i = A^{+}$ then $C_{i*} = 1$, and if $A_i = A^{-}$ then $C_{i*} = 0$.

Step 7: Finally, the last step in the TOPSIS method involves ranking the options. In this step, the options are sorted and ranked in descending order (Yoon & Hwang, 1995; Yue, 2011).

K-means Clustering Algorithm

This study applied *K*-means clustering algorithm to analyze food consumption patterns in rural areas and identify provinces with similar behavioral patterns. In this method, *K* random members are selected from among the members as the coordinates of the cluster centers. Then, the distance of the points (members) from the centers is calculated, and each member is assigned to the cluster with the closest center. The steps for performing the *K*-means clustering method are summarized as follows (Luo, 2022):

- First, the value of *k* is determined, and then *k* sets are extracted through clustering. Depending on the volume of data, the value of *k* can vary between 3 and 6.
- By determining the value of *k*, data is randomly selected from the data set and assigned to cluster centers (c_i's).
- Then, the Euclidean distance of each point from the cluster center is calculated. If this distance is small, that point is assigned to the set to which that center belongs.
- After the data set is allocated, a total of *k* clusters is formed. At this stage, the center of each cluster is recalculated.
- If the distance between the newly calculated center and the previous center is less than a certain threshold, this indicates a small change in the center and a tendency to converge; hence, it can be concluded that the clustering was performed satisfactorily and the results of the algorithm are optimal.

The *K*-means clustering algorithm can be represented as Equation (9).

$$\boldsymbol{SSE} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \sum_{\boldsymbol{x \in c_i}} \boldsymbol{dist}(\boldsymbol{c_i}, \boldsymbol{x}) \qquad (9)$$

In the above relation, *k* represents the number of clusters, while c_i represents the center of cluster *i*. Finally, *dist* represents the Euclidean distance between two points (Liu, 2022).

In this study, the household calorie intake criterion from ten commodity groups, including bread and cereals, fish and shellfish, oils and fats, vegetables and legumes, red meat and poultry, milk, cheese and eggs, fruits and nuts, sugar and sweets, beverages and non-alcoholic beverages, and food products not elsewhere classified, was used to cluster provinces and identify provinces with similar patterns of food consumption in rural areas. The study followed common approaches for clustering. First, the number of clusters was determined using the hierarchical cluster analysis method, and then the K-means method was used to form the clusters. Initially, the principal component score (PCS) was obtained using the principal component analysis (PCA) method. The PCS was then used in the framework of hierarchical cluster analysis and the Ward clustering method to calculate Agglomerative clustering. In aggregate clustering, the data was initially considered as separate clusters, and during an iterative process at each stage, the clusters that were more similar to each other were combined to finally determine the number of clusters.

After clustering the provinces, the study finally analyzed the reasons for the distribution of food consumption patterns in rural areas of Iran. To achieve this, the relationship between food consumption patterns and the infrastructural, economic, and social indicators of the provinces was examined. It is important to note that the research conducted by Parsipoor *et al.* (2022) was used to determine the status and ranking of the provinces in terms of infrastructural, economic, and social indicators[1].

Results and Discussion

Current Food Consumption Pattern in Rural of Iran

Fig. 1 depicts the distribution of various commodity groups in the dietary habits of rural areas in Iran in the year 2023. According to the data presented, in 2023, 60.3% of an adult's caloric intake in rural Iran originated from bread and grains, 5.6% from red meat and poultry, 0.2% from fish and seafood, 5.1% from dairy products and eggs, 12% from oils and fats, 3.7% from fruits and nuts, 6.3% from vegetables and legumes, 6.2% from sugar and sweets, 0.01% from non-alcoholic beverages like tea and coffee, and a mere 0.7% from other

[1]- In the study by Parsipoor *et al*. (2022), 8, 12, and 6 sub-indices were defined for infrastructural, economic, and social indicators, respectively, to determine the rank of different provinces.

food products. The data from Fig. 1 highlights that the predominant dietary pattern in rural Iranian households revolves around various cereal types, accounting for over 60% of an adult's daily energy intake. Comparatively, globally, cereals typically contribute 50% of daily calorie requirements, with percentages varying at 30%, 55%, and 70% in high-, middle-, and low-income countries, respectively. This disparity between Iran's rural areas and the global average suggests a reliance on cereals, which are deemed low in nutritional value, to fulfill a significant portion of daily caloric needs. Rather than incorporating more nutrient-rich foods like fruits, vegetables, and meats, individuals have leaned heavily on grains. Research by Shabanzadeh-Khoshrody *et al.* (2024) suggests that this phenomenon may stem from a mix of economic and non-economic factors, including cultural eating habits, easy grain accessibility, and cost comparisons between grains and other food items. Identifying and analyzing the food basket in different provinces of Iran, especially in rural areas, can help us better understand the challenges and opportunities in ensuring food security and promoting community health. Provinces with a standard food basket can not only indicate access to diverse and nutritious food sources but also serve as models for improving food systems in other regions. Additionally, the consumption pattern and corresponding diet of each province can directly impact the overall health of the people in that region. Understanding consumption patterns can help identify health and nutritional problems, allowing the government and relevant institutions to make better plans to ensure food security, improve nutrition, and address health issues.

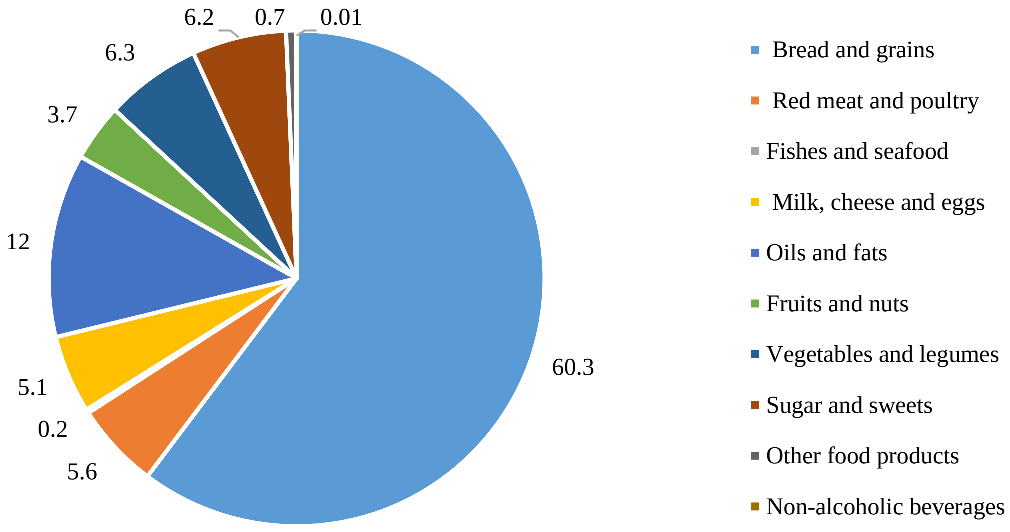

Figure 1- The share of commodity groups in the consumption of Iranian rural households in 2023

Comparative Analysis of Current and Standard Food Basket

A proper food basket helps meet the body's basic needs, such as protein, vitamins, minerals, and energy, and prevents health problems. Accordingly, in this section, the current food basket is compared with the standard food basket proposed by the Ministry of Health and Medical Education of Iran. It is designed to meet 100 percent of the household's energy needs and at least 80 percent of the five key nutrients. If a person consumes the items in this basket, they will consume 1563 grams of food daily and receive 2573 kilocalories of energy. However, as is clear from the information in Table 2, in the current situation, consumption does not follow the standard pattern. People in rural areas of Iran, on average, obtain only 2162 kcal of energy by consuming 1119 grams of food. In other words, we can say that people are currently consuming 28.4% less of the standard food basket and receiving 16% less of the required amount of energy. In this context, as is clear, only in the area of bread consumption do people consume more than the standard amount, and the consumption of other foods is less than the standard level.

According to a study by Vaez Mahdavi *et al*. (2022), the high consumption of bread in Iran has various reasons, with the most important being its affordability compared to other food items. This situation also applies, to some extent, to vegetable oils and sugar. In Table 2, lower per capita consumption of sugar, flour, and oil than the standard level does not necessarily mean that households consume less of these items. This discrepancy arises because the calculations only consider direct household consumption. Households also consume sweets, fast foods, and other products that use significant amounts of sugar and oil in their production process. Therefore, when considering these factors, it becomes evident that the per capita consumption of sugar and oil is higher than indicated in Table 2, if indirect consumption is taken into account. A review of Iran's laws, policies, and programs reveals that a significant portion of the country's resources are allocated each year to direct and indirect subsidies for essential foods and major energy-producing goods such as bread, sugar, and oil. These items benefit from special government support policies aimed at stabilizing prices and protecting consumers. This focus on these staple foods has resulted in an increase in the prices of meat and dairy products, which have replaced starchy and energy-rich products in the household food basket. Table 2 illustrates a concerning trend, showing a significant disparity between per capita and standard consumption of dairy products, fruits, and red meat. The data indicates that the recommended daily intake for each person is 250 grams of dairy products, 280 grams of fruit, and 38 grams of red meat. However, current consumption levels in rural areas of Iran fall short of these standards by 64.4 percent, 52.1 percent, and 50 percent, respectively. Given the nutritional value of these foods, the reduced consumption levels raise serious health concerns for individuals in rural areas of Iran.

The results of Table 2 show that the current food consumption pattern in rural areas of Iran significantly deviates from the standard pattern.

Ranking Consumption Pattern

According to the results of Table 3, six provinces - Chaharmahal and Bakhtiari, Markazi, Isfahan, Hamedan, Zanjan, and Mazandaran - have the highest ranking in terms of dietary patterns in rural areas, being closer to the standard dietary pattern provided by the Ministry of Health. Conversely, among the provinces of Iran, the dietary pattern in rural areas of Hormozgan, Semnan, Kerman, North Khorasan, Ilam, and Sistan and Baluchestan is the furthest from the standard food basket recommended by the Ministry of Health. A study of these provinces reveals that those with consumption patterns closer to standards have a relatively better economic situation, with higher purchasing power among residents. Additionally, weather conditions, climatic, and geographical characteristics have contributed to the diversity in agricultural and livestock production in these regions, leading to a more balanced consumption pattern.

Food consumption patterns in different provinces typically vary due to cultural, climatic, economic, and social distinctions. Understanding these patterns can assist policymakers in better planning for food supply, ensuring food security, and reducing food price volatility.

Table 2- Comparison of the current and standard food basket in rural areas of Iran

Food	Current situation		Standard situation		Difference	
	Consumption per capita (grams per day)	Energy (kilocalorie)	Consumption per capita (grams per day)	Energy (kilocalorie)	Consumption per capita (%)	Energy (%)
Bread	335	950	310	879	8.1	8.1
Rice	79	282	95	339	-16.8	-16.8
Macaroni	11	40	20	72	-45	-44.4
Legumes	17	60	26	91	-34.6	-34.1
Potato	60	49	70	57	-14.3	-14
Vegetables	234	66	300	85	-22	-22.4
Fruits	134	67	280	141	-52.1	-52.5
Red meat	19	53	38	106	-50	-50
Poultry	55	70	64	82	-14.1	-14.6
Egg	20	26	35	45	-42.9	-42.2
Dairy products	89	74	250	207	-64.4	-64.3
Vegetable oils	33	297	35	315	-5.7	-5.7
Sugar	33	128	40	155	-17.5	-17.4
Total	1119	2162	1563	2573	-28.4	-16

Source: Ministry of Health, Treatment and Medical Education of the Islamic Republic of Iran (2012) and research findings.

Table 3- The degree of proximity to the desired food basket in rural areas of Iran

Province	Score	Rank
Chaharmahal and Bakhtiari	0.851	1
Markazi	0.689	2
Isfahan	0.610	3
Hamadan	0.570	4
Zanjan	0.561	5
Mazandaran	0.560	6
Kurdistan	0.560	7
Qazvin	0.548	8
Yazd	0.542	9
Kohgiluyeh and Boyer-Ahmad	0.529	10
Alborz	0.525	11
Fars	0.523	12
Tehran	0.514	13
Khuzestan	0.507	14
South Khorasan	0.505	15
Lorestan	0.487	16
Bushehr	0.486	17
Ardabil	0.478	18
Kermanshah	0.476	19
West Azerbaijan	0.459	20
Golestan	0.422	21
Qom	0.406	22
Gilan	0.401	23
East Azerbaijan	0.400	24
Razavi Khorasan	0.393	25
Hormozgan	0.392	26
Semnan	0.302	27
Kerman	0.293	28
North Khorasan	0.265	29
Ilam	0.262	30
Sistan and Baluchestan	0.229	31

Source: Research findings

Cumulative clustering

The results of cumulative clustering are presented in Table 4. In this study, a notable mutation was observed at stage 26 out of 31 provinces, suggesting 5 clusters as the optimal number based on the difference between these two numbers.

Table 4- Results of cumulative clustering

Stage	Combined cluster		Coefficients	Difference of coefficients
	Cluster 1	Cluster 2		
1	1	19	2082	-
2	20	27	4252	1147
3	4	5	6439	1320.5
4	24	25	8701	1570
5	23	26	11000	1691.5
6	18	31	13760	1725
7	17	30	16907	1801
8	2	13	20199	1918
9	11	21	24288	2183
10	14	20	28703	2266.333
11	10	18	33461	2880.334
12	2	22	39704	3049.333
13	6	12	47228	3369
14	8	14	55470	4139.667
15	6	15	65368	4827
16	17	28	76025	5260.333
17	4	10	86697	5991.367
18	23	24	98924	6565.25
19	2	29	111454	6868.416
20	11	16	124693	7155
21	7	8	146421	9625.4
22	3	6	169700	10848
23	1	7	194210	14875.53
24	1	23	229489	15750.37
25	4	17	270423	26543.09
26	2	9	283889	32333.05
27	1	11	1019361	50075.1
28	2	4	2598150	56660.81
29	1	3	2792260	98166.19
30	1	2	2808681	292320.7

The third column of the table represents the coefficients, while the fourth column shows the differences between coefficients at various clustering stages. Significant changes in mutation coefficients between stages indicate the optimal number of clusters.
Source: Research findings

Table 5 identifies the provinces located in different clusters. Meanwhile, Fig. 2 shows a map of food consumption in urban areas of various provinces of the country based on the clustering in Table 5. It is evident from the Table 5 and Figure 2 that the food consumption patterns in rural areas of different provinces of the country are diverse and heterogeneous, with five distinct behavioral patterns. The food consumption pattern in rural areas of Iran appears to have little correlation with the geographical location of the provinces. For instance, provinces in the third cluster, such as Ardabil, Ilam, and North Khorasan, are situated in the western and eastern parts of the country and do not share a common border with each other. Additionally, as indicated in Table 6, a common characteristic of rural areas in all provinces is the below-standard consumption of essential food items like fruits, vegetables, meat, and dairy products. Provinces in the first cluster align more closely with the standard food consumption pattern than those in the other clusters, while those in the fifth cluster deviate the most from the standard pattern recommended by the Ministry of Health.

Table 5- Provinces located in different clusters

Clusters	The number of cluster members	Provinces
Cluster 1	9	Bushehr, Tehran, Zanjan, Fars, Kurdistan, Lorestan, Mazandaran, Markazi, Hamedan
Cluster 2	4	West Azerbaijan, Chaharmahal and Bakhtiari, Khuzestan, Kohgiluyeh and Boyer-Ahmad
Cluster 3	6	East Azerbaijan, Ardabil, Ilam, North Khorasan, Semnan, Qom
Cluster 4	10	Isfahan, Alborz, South Khorasan, Razavi Khorasan, Qazvin, Kermanshah, Golestan, Gilan, Hormozgan, Yazd
Cluster 5	2	Sistan and Baluchestan, Kerman

Source: Research findings

Table 6- The state of the food pattern of different clusters (grams per day)

Clusters	Sugar	Vegetable oils	Dairy products	Egg	Poultry	Red meat	Fruits	Vegetables	Potato	Legumes	Macaroni	Rice	Bread
Cluster 1	37	36	106	22	61	21	158	296	68	20	15	94	356
Cluster 2	31	31	102	17	52	12	128	243	63	12	11	76	133
Cluster 3	32	30	90	19	50	20	121	214	63	17	9	62	526
Cluster 4	29	32	83	21	58	20	144	209	57	17	11	75	300
Cluster 5	39	29	39	10	44	7	50	152	39	16	5	56	354

Source: Research findings

Relationship between Food Consumption Patterns and Infrastructural, Economic and Social Indicators

The distribution of food consumption patterns in rural areas of Iran can have various reasons. In Table 7, the relationship between food consumption patterns and the infrastructural, economic and social indicators of the provinces is examined. Table 7 is divided into two sections; values above the average and values below the average. Values above the average indicate provinces that rank higher than the overall average in the desired indicator, and vice versa. As is clear from the table, on average, provinces with higher infrastructural, economic, and social indicators have higher average scores in the TOPSIS ranking and therefore have a more standardized food consumption pattern. Regarding the results obtained, it should be noted that infrastructure indicators, especially the existence of appropriate transportation infrastructure, facilitate access to markets and distribution of products. This can lead to a variety of food standards. Economic indicators, including higher income levels, usually lead to better food security and the ability to purchase a wider variety of products. In addition, strong local markets, diverse jobs, support for diverse agriculture, and appropriate government policies can contribute to adequate food consumption. Ultimately, social indicators, including the food culture and customs of each region, have a great impact on food consumption patterns. Some regions may have a richer food culture that contributes to the production and consumption of more diverse foods. Awareness, education, family, and social patterns are other cultural factors that can influence dietary behaviors by contributing to healthy nutrition and dietary diversity.

Conclusion and suggestions

A detailed study and analysis of food consumption patterns in rural areas of Iran can not only help identify standard patterns, but also serve as a tool for developing innovative strategies to improve the quality of nutrition and livelihoods in these areas. As a result, paying special attention to this issue can be considered a key measure towards sustainable development and improving the quality of life in different parts of the country.

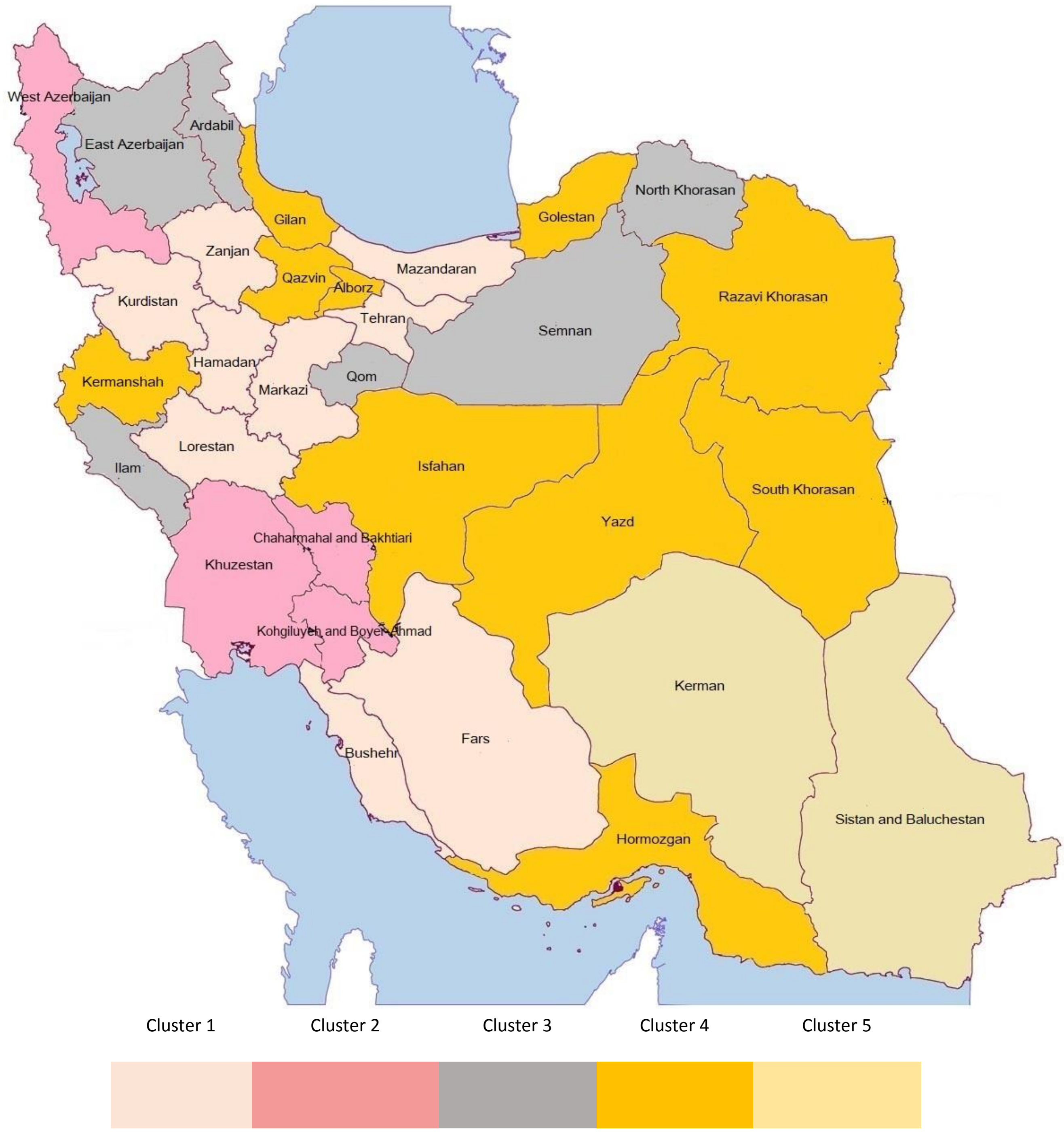

Figure 2- Map of food consumption pattern in rural areas of Iran

In this study, household income-expenditure data from the Statistical Center of Iran was used to examine the current pattern of food consumption in rural areas of Iran for the year 2023 and compare it with the standard pattern.

Table 7- Relationship of the food consumption patterns and infrastructural, economic and social indicators of provinces in Iran

Indicators	Upper of average		Under of average	
	Provinces	**TOPSIS Score in TOPSIS ranking**	**Provinces**	**TOPSIS Score in TOPSIS ranking**
Infrastructure indicators	Tehran, Isfahan, Khorasan Razavi, Bushehr, Fars, Alborz, Khuzestan, Mazandaran	0.515	East Azerbaijan, Yazd, Kerman, Gilan, Hormozgan, Semnan, Qazvin, Markazi, Qom, Hamedan, West Azerbaijan, Kurdistan, Kermanshah, Chaharmahal and Bakhtiari, Ardabil, Zanjan, Golestan, Lorestan, Ilam, South Khorasan, North Khorasan, Kohkiluyeh and Boyer Ahmad, Sistan and Baluchestan	0.462
Economic indicators	Tehran, Isfahan, Khorasan Razavi, Bushehr, Fars, Alborz, Khuzestan, Mazandaran, East Azerbaijan, Yazd, Kerman, Hormozgan	0.479	Gilan, Semnan, Qazvin, Markazi, Qom, Hamedan, West Azerbaijan, Kurdistan, Kermanshah, Chaharmahal and Bakhtiari, Ardabil, Zanjan, Golestan, Lorestan, Ilam, South Khorasan, North Khorasan, Kohkiluyeh and Boyer Ahmad, Sistan and Baluchestan	0.474
Social indicators	Tehran, Isfahan, Khorasan Razavi, Bushehr, Kurdistan, Alborz, Khuzestan, Mazandaran, East Azerbaijan, Yazd, Semnan, Qom, Zanjan, Markazi, Hamedan, Qazvin	0.508	Gilan, Kerman, Hormozgan, Fars, West Azerbaijan, Kermanshah, Chaharmahal and Bakhtiari, Ardabil, Golestan, Lorestan, Ilam, South Khorasan, North Khorasan, Kohkiluyeh and Boyer Ahmad, Sistan and Baluchestan	0.446

Source: Research findings

Provinces whose dietary patterns are closest to the standard pattern were identified and ranked using the TOPSIS method. Additionally, using the k-means clustering method, provinces with similar food consumption patterns were extracted, and a map of the food consumption patterns of rural areas of Iran was drawn. Finally, the relationship between food consumption patterns and the infrastructural, economic, and social indicators of the provinces was examined. The results showed that the current dietary pattern of households in rural areas of Iran mainly consists of various types of cereals, providing more than 60% of the daily energy needs of an adult. Globally, cereals contribute to 50% of daily calories, with proportions of 30%, 55%, and 70% in high-, middle-, and low-income countries, respectively. Currently, food consumption in rural Iran deviates from the standard pattern, with individuals consuming 28.4% less food items than recommended and receiving 16% less energy than needed. While bread consumption exceeds the standard amount, dairy products, fruits, and red meat consumption fall short by 64.4%, 52.1%, and 50% respectively. These findings align with a study by Forouhesh & Soltani (2024) on changing food consumption patterns in Iranian households since the 1960s. The incorrect food consumption pattern in Iran stems from economic and non-economic factors. To address this, efforts should focus on increasing income, stabilizing food prices, and implementing programs to improve physical access and promote healthy eating habits. Experiences from other countries suggest that these strategies can effectively shift consumption patterns and increase food intake, particularly of nutrient-rich foods. Based on the results, the dietary pattern in rural areas of six provinces - Chaharmahal and Bakhtiari, Markazi, Isfahan, Hamedan, Zanjan, and Mazandaran - is closer to the standard dietary pattern provided by the Ministry of Health. Conversely, the dietary pattern in rural areas of the provinces of Hormozgan, Semnan, Kerman, North Khorasan, Ilam, and Sistan and Baluchestan is the farthest from the recommended standard food basket by the Ministry of Health. The results suggest that provinces with dietary patterns aligning with the Ministry of Health's standards should be highlighted as successful examples. Analyzing the factors contributing to the success of these provinces can assist policymakers in implementing solutions to improve food consumption in other regions. Based on the results of the study, the food consumption patterns in rural areas of different provinces in the country are heterogeneous and highly diverse, with five distinct behavioral patterns identified. Interestingly, the food consumption patterns in rural areas of Iran do not seem to be closely tied to the geographical location of the provinces. On average, provinces with higher infrastructural, economic, and social indicators exhibit a more standardized food consumption pattern. These findings closely align with a study conducted by Rastegaripour *et al*. (2021) on the impact of economic and social factors on the consumption habits of rural and urban households in Iran. The results suggest that improving infrastructure indicators, such as developing economic infrastructure like processing industries and markets in rural areas, can lead to the creation of new job opportunities. With increased employment, people's purchasing power rises, subsequently influencing their food consumption choices. In addition, improving social indicators, such as increasing levels of education and access to information in rural areas, can lead to improved dietary patterns and healthier food choices. People who are more aware of healthy eating and the importance of dietary diversity are able to improve the quality of the food they consume. Improving transportation infrastructure also provides rural residents with access to larger markets, which can increase food diversity and availability. Considering the positive impact of infrastructure, economic, and social indicators on food consumption in rural areas of Iran, it is suggested to strengthen the transformation and processing industries by supporting the establishment of food processing workshops in rural areas. Additionally, increasing employment opportunities, especially through the creation of non-agricultural jobs in handicraft industries, tourism, and services in rural areas, should be prioritized. Furthermore, increasing investment in infrastructure, such as building and improving roads and bridges, to facilitate access to markets and shopping centers is recommended. Enhancing access to education and information through nutrition classes and educating on smart food purchasing methods, as well as utilizing media and cyberspace to raise awareness of healthy eating, are crucial factors to consider due to their impact on people's nutritional habits and culture.

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مقاله پژوهشی

جلد ۳۹، شماره ۲، تابستان ۱۴۰۴، ص. ۲۱۰-۱۹۳

تحلیل الگوی مصرف مواد غذایی در مناطق روستایی ایران: شناسایی استان‌های با مصرف استاندارد و همگن

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تاریخ دریافت: ۱۴۰۳/۱۱/۲۱
تاریخ پذیرش: ۱۴۰۴/۰۲/۰۶

چکیده

بررسی الگوی مصرف غذا در مناطق روستایی ایران برای درک وضعیت امنیت غذایی و رفاه اجتماعی در کشور ضروری است. شناسایی استان‌های دارای الگوی مصرف استاندارد و همگن، نه تنها به برنامه‌ریزی برای تأمین نیازهای غذایی کمک می‌کند، بلکه می‌تواند به تدوین سیاست‌های مناسب و مؤثر در راستای حل مسائل مرتبط با تغذیه و بهداشت عمومی نیز منجر شود. با این رویکرد در این مطالعه، ابتدا الگوی فعلی مصرف غذا در مناطق روستایی ایران در سال ۱۴۰۲ مورد بررسی قرار گرفت و با الگوی استاندارد مقایسه شد. سپس، استان‌هایی که الگوی غذایی آن‌ها شباهت بیشتری به الگوی استاندارد دارد، با استفاده از روش TOPSIS شناسایی و رتبه‌بندی شدند. پس از آن، با بهره‌گیری از روش خوشه‌بندی k-means، استان‌های با الگوی مصرف مشابه استخراج و نقشه‌ی الگوی مصرف غذا برای مناطق روستایی ایران ترسیم گردید. در نهایت، رابطه بین الگوی مصرف و شاخص‌های زیرساختی، اقتصادی و اجتماعی استان‌ها مورد تحلیل قرار گرفت. نتایج نشان داد که الگوی غذایی کنونی خانوارها در مناطق روستایی ایران عمدتاً شامل غلات است و این گروه بیش از ۶۰ درصد انرژی روزانه را تأمین می‌کند. در حالی‌که در سطح جهانی، سهم غلات در تأمین کالری روزانه معادل ۵۰ درصد است و این نسبت در کشورهای با درآمد بالا، متوسط و پایین، به‌ترتیب ۳۰، ۵۵ و ۷۰ درصد می‌باشد. علاوه بر این، در شرایط کنونی، مصرف غذا در ایران مطابق با الگوی استاندارد نیست و ساکنان مناطق روستایی کشور ۲۸/۴ درصد کمتر از مواد غذایی سبد استاندارد استفاده می‌کنند و همچنین ۱۶ درصد کمتر از انرژی مورد نیاز را دریافت می‌نمایند. افراد بیشتر از نیاز خود نان مصرف می‌کنند، اما در خصوص لبنیات، میوه‌ها و گوشت قرمز، مصرف کنونی به‌ترتیب ۶۴/۴، ۵۲/۱ و ۵۰ درصد پایین‌تر از مقدار استاندارد است. الگوی غذایی در مناطق روستایی شش استان چهارمحال و بختیاری، مرکزی، اصفهان، همدان، زنجان و مازندران به استاندارد تعیین‌شده توسط وزارت بهداشت نزدیک‌تر است. در مقابل، الگوی غذایی در نواحی روستایی شش استان هرمزگان، سمنان، کرمان، خراسان شمالی، ایلام و سیستان و بلوچستان بیشترین فاصله را با سبد غذایی استاندارد دارد. از سوی دیگر، الگوی مصرف مواد غذایی در مناطق روستایی استان‌ها متنوع و ناهمگون است و می‌توان پنج نوع الگوی رفتاری را شناسایی کرد؛ بر اساس نتایج، الگوی مصرف در مناطق روستایی ایران با موقعیت جغرافیایی ارتباط چندانی ندارد و استان‌هایی که شاخص‌های زیربنایی، اقتصادی و اجتماعی مناسب‌تری دارند، از الگوی مصرف غذایی استانداردتری برخوردار هستند. با توجه به تجربیات کشورهای مختلف، بهبود تغذیه در مناطق روستایی فرآیندی چند بعدی است و تحت تأثیر مجموعه‌ای از متغیرها شامل عوامل اقتصادی (مانند درآمد، قیمت مواد غذایی، نرخ بیکاری و ...)، عوامل منطقه‌ای (از جمله دسترسی به غذا، توسعه زیرساخت‌های حمل و نقل، شرایط آب و هوایی و ...)، عوامل اجتماعی و فرهنگی (شامل فرهنگ و باورهای اجتماعی، سطح آموزش و آگاهی، شبکه‌های اجتماعی و ...) و نهایتاً عوامل فردی (مانند سلامت فردی، عادات و رفتارهای غذایی، دانش شخصی و ...) قرار دارد و برای دستیابی به یک الگوی تغذیه‌ای سالم و متوازن، باید به تعامل و هم‌افزایی میان این عوامل توجه جدی نمود.

واژه‌های کلیدی: سبد غذایی فعلی و استاندارد، نواحی روستایی ایران، الگوی رفتاری مشابه، روش TOPSIS، خوشه‌بندی k-means

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https://doi.org/10.22067/jead.2025.92120.1333

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Agricultural Economics & Development

(AGRICULTURAL SCIENCES AND TECHNOLOGY)

Vol. 39 No.2 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

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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.39 No.2

2025

ISSN:2008-4722

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