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Influence of Mental Models on Sustainable Wheat Seed Use: A Comparative Study in Western Iran

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Abstract

Understanding farmers' mental models (MM) is crucial for interpreting their behavior; however, these models, are shaped by technical, economic, and social factors, have often been overlooked. Using a case study from Kangavar County, Western Iran, this study investigates the MM of farmers and experts regarding wheat seed usage and proposes optimization strategies using a mixed-methods approach. Qualitatively, phenomenological analysis of interviews with 16 participants (selected via purposive and snowball sampling) identified five key factors shaping farmers' mental models (MM): work context, climate, experienced risks, available resources, and subjective norms. Experts' rationale for seed recommendations centered on three themes: academic knowledge, professional experience, and user characteristics. Quantitatively, a structured questionnaire administered to a separate sample of 255 farmers (stratified proportional sampling) and 50 experts (complete enumeration) revealed significant disparities. Independent samples t-tests revealed statistically significant differences ($p < 0.01$) across all major mental model (MM) domains. Responses were initially scored as percentages (0–100) based on item agreement, then standardized to a 100-point scale. Mean scores were substantially higher among farmers in experienced risks (74.02 vs. 15.80), subjective norms (66.24 vs. 18.93), and work context (65.67 vs. 35.30), indicating stronger perceived influence of experiential and social factors. Conversely, experts scored higher on academic knowledge (75.28 vs. 41.71), reflecting greater reliance on scientific evidence.The Delphi method identified and prioritized key strategies for optimizing seed use, with "preparing a suitable seedbed" (weighted average: 0.148) and "using certified seeds" (weighted average: 0.143) ranked highest. These findings underscore the critical gap between farmer and expert models and emphasize the need for targeted interventions that integrate experiential knowledge with scientific evidence to bridge this divide, fostering more sustainable seed usage practices.

Keywords: Cognitive decision-making, Delphi technique, Mental models, Mixed-methods, Phenomenological study, Sustainable wheat production

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Introduction

Achieving sustainable agricultural development hinges on optimizing the use of critical inputs, with seeds representing the biological cornerstone of crop production and global food security (Bist *et al.*, 2021). However, a persistent challenge in agricultural extension is the frequent divergence between scientifically recommended practices and the actual decisions made by farmers. This gap is often attributed not to a lack of information, but to the deeply held cognitive frameworks, or mental models, that guide farmers' perceptions and actions (Jones *et al.*, 2011; Moon *et al.*, 2019). These internal representations of reality, synthesized from personal experience, social norms, and contextual factors, form the lens through which farmers interpret risks, opportunities, and advice (Johnson-Laird, 2010). Despite their profound influence on farm management outcomes, the specific structure and content of farmers' mental models, particularly concerning input use like seeds, remain underexplored in research and poorly integrated into policy design (Olivier de Sardan, 2005; Levy *et al.*, 2018).

Seeds are crucial agricultural input where mental models play a pivotal role. Seeds are the biological foundation of global food security and directly affect human livelihoods (Bist *et al.*, 2021). The availability of suitable seeds and their correct usage are vital for optimizing agricultural performance per unit area (Zareyan *et al.*, 2011). Given the strategic importance of wheat, which is not only a major source of income but also a key factor in political and economic relations (Abolhassani *et al.*, 2018), understanding the MM related to wheat seed consumption is essential. Iran, which represents 1% of the world's population, consumes 2.5% of the world's wheat, with over 60% of the country's arable land dedicated to wheat cultivation. In the 2019-2020 agricultural year, Iran's cultivated crop area was approximately 12.192 million hectares, with 71% (8,658,095 hectares) allocated to grain crops, and wheat accounted for 69.3% of this area. Wheat also constitutes 58.6% of the total grain production (Statistical Center of Iran, 2021). In Kermanshah Province, western Iran, the recommended seed amount for rain fed wheat is 150 kg per hectare and for irrigated wheat, 200 to 250 kg (Haghparast, 2013). However, actual seed consumption often exceeds these recommendations, reaching 200–300 kg for rainfed wheat and 250–400 kg for irrigated wheat (Argha *et al.*, 2021). This overconsumption significantly impacts the agricultural economy, particularly in Kangavar County, where wheat cultivation covers 4,900 hectares of irrigated and 6,300 hectares of rainfed land. Excessive seed use could cost the agricultural sector between 40 and 70 billion Rials annually (Khazaei, 2021).

This study makes a novel contribution to the existing literature by focusing on the mental models that shape farmers' wheat seed consumption practices, an area that has received limited attention compared to technical aspects such as seed purity, germination, or varietal selection (Argha *et al.*, 2021). By employing a mixed-methods approach, we provide a comprehensive analysis of the cognitive frameworks of both farmers and agricultural experts in Kangavar County, Western Iran, and shedding light on the behavioral and psychological drivers of seed overconsumption. Furthermore, our study advances the field by identifying consensus-driven strategies to optimize wheat seed use, offering practical solutions to enhance agricultural sustainability and economic efficiency in regions heavily reliant on wheat production. This focus on mental models and actionable strategies addresses a critical gap in understanding how cognitive factors influence resource use in agriculture, contributing to both theoretical and applied dimensions of sustainable farming practices. This approach offers a novel perspective for developing targeted interventions to bridge the gap between recommended and actual seed use, a critical issue for sustainable wheat production. Given the strategic role of wheat in Iran's food security and its contribution to national development goals, optimizing seed use is crucial. With limitations in expanding production factors or implementing major technological changes, improving the efficiency of existing resources, especially seeds, is vital. Gathering comprehensive information on the factors affecting field coverage and understanding farmers' MM regarding seed consumption can lead to more accurate planting practices and significant economic savings. Therefore, this research presents a focused case study of Kangavar County, a key wheat-producing area in Kermanshah Province, Western Iran to identify the factors shaping farmers' MM and provide strategies to effectively reduce wheat seed consumption.

Literature review

Mental Models (MM) and Factors Influencing Their Formation

Mental models are cognitive representations that individuals construct to understand, interpret, and predict phenomena in their environment. These models consist of interconnected knowledge, experiences, beliefs, values, and assumptions that simplify complex realities and enable reasoning about unfamiliar situations (Moon *et al*., 2019). In agriculture, mental models profoundly influence farmers' decision-making processes by acting as filters for incoming information, shaping perceptions of risks and opportunities, and guiding behavioral responses to challenges such as resource allocation, climate variability, and input usage. For instance, farmers may rely on these models to evaluate trade-offs in seed consumption, prioritizing experiential heuristics over expert recommendations, which can lead to suboptimal practices if the models are misaligned with scientific evidence (Bartaburu *et al*., 2022).

Mental models are internal representations of reality that help individuals understand and reason about situations, even those they have not directly experienced (Jones *et al*., 2011). These models consist of deeply ingrained assumptions and generalizations that shape our perception of the world and guide our actions (Marques, 2014). However, these models are often based on generalizations that may not always be accurate, leading to widespread misunderstandings (Johnson-Laird, 2010). Two main approaches are used to study MM: one focuses on the knowledge and processes involved in reasoning within specific domains (Todorovikj *et al*., 2019), while the other views MM as constructs in working memory that support logical reasoning. Generally, people develop these models through interactions with their environment and others, which help them understand and predict various phenomena (Johnson-Laird, 2010). Mental models are crucial cognitive structures that influence reasoning processes. They act as a set of hierarchical rules that function competitively and cooperatively. However, individuals are often unaware of their MM and how these affect their performance and decision-making. Researchers study these models by analyzing behavior rather than asking direct questions, as MM often operate at a subconscious level. These cognitive structures, which include attitudes, emotions, and beliefs, serve as lenses through which individuals perceive the world and influence how they interpret and react to different situations. As a result, two people might perceive the same event differently based on their unique mental models (Lee & Webb, 2005; Suomala & Kauttonen, 2022; Holtrop *et al*., 2020). Overall, MM are essential for understanding how individuals make decisions and interact with their world. They are dynamic systems within the mind that process external information, leading to actions based on internal cognitive structures (Jones *et al*., 2011; Chermack, 2003; Capelo & Dias, 2009). Previous studies have employed a variety of methods to elicit and analyze mental models, including semi-structured interviews to capture farmers' cognitive frameworks through narrative responses (Eckert & Bell, 2005), questionnaires to quantify differences in perceptions across groups (Halbrendt *et al*., 2014), and behavioral analysis to infer models from observed decision-making patterns (Levy *et al.*, 2018). More recent approaches have incorporated innovative techniques such as values-informed mental modeling, which integrates epistemic values into interviews and cognitive mapping to understand stakeholder perceptions of complex systems like water management (Afzal *et al.*, 2025), and drawing-based elicitation methods to visualize and compare mental models of human-nature relationships in agricultural contexts (Morrison *et al.*, 2024). More recently, behavioral analysis and experimental games have been used to infer mental models from observed actions rather than stated beliefs, helping to circumvent social desirability bias (Bartaburu *et al.*, 2022). Recognizing that each method has limitations, a mixed-methods approach as adopted in this study is increasingly advocated. This approach leverages the depth of qualitative inquiry to ensure the relevant constructs are captured, followed by quantitative measures to validate and generalize findings, thereby providing a more comprehensive understanding (*Jones et al.*, 2011; Levy *et al.*, 2018).

Mechanisms Linking Contextual Factors to Mental Model Formation

Recently research has begun to delineate the precise cognitive mechanisms through which contextual factors shape farmers' mental models. These factors do not influence decisions directly but are filtered and interpreted through pre-existing cognitive frameworks, which are subsequently reinforced or updated (Moon *et al.*, 2019; Lynam & Brown, 2011). For instance, climate-related experiences, particularly extreme events like drought, operate primarily through the mechanism of experiential learning and risk amplification (Gebrehiwot & Veen, 2020). Repeated exposure to crop loss from drought can lead to an overestimation of climatic risk, causing farmers to adopt defensive heuristics such as "more seeds equal more security" that become entrenched in their mental models (Kansiime *et al.*, 2021; Guido *et al.*, 2020). Similarly, limitations in facilities and equipment shape farmers’ mental models through perceived affordances and constraints. When equipment is imprecise, farmers learn to compensate by overseeding in order to achieve acceptable plant density, a practice that gradually becomes a normalized “workaround” (Feola et al., 2015). Over time, this practical adaptation can evolve into a core belief about what is necessary, overshadowing knowledge of optimal seeding rates.Subjective norms exert their influence through the mechanism of social learning and normative conformity (Bandura, 1977; Ajzen, 1991). In close-knit agricultural communities, observing peers and adhering to traditional practices provides social validation and reduces perceived social risk. When a practice like high seed consumption is widespread, it creates a descriptive norm that individuals are cognitively motivated to follow, integrating it into their mental model as a "correct" way of farming (Hansson & Kokko, 2018; Hoppe *et al.*, 2023). Understanding these mechanisms experiential learning, affordance-based adaptation, and social conformity helps explain not just what factors influence mental models, but how they become cognitively embedded and resistant to change.

Mental Models (MM) in Agriculture

When considering an agricultural system, it becomes evident that farming encompasses more than just plants, soil, and farm inputs. It also involves soil organisms, wildlife, water resources, runoff, and, crucially, the farmers themselves (Keating & McCown, 2001). However, the extent of farmers' engagement in environmental systems thinking and how this influences their on-farm decision-making and behaviors require further research (Azizi *et al.*, 2022). Understanding these agricultural systems, including how factors and their relationships are defined, can be developed by exploring mental models, which are frameworks that people use to understand their world (Ghanbari *et al.*, 2018). Mental models are utilized for everyday decision-making and are shaped by knowledge acquisition and experience (Grenier & Dudzinska-Przesmitzki, 2015).

For farmers, this knowledge often evolves over time through social learning processes, where information is shared with extension agents, scientists, and other industry partners during meetings, outreach events, and informal settings, such as farmer-to-farmer communication, all of which influence their decisions and preferences. Social learning processes may be key to sustainability in natural resource management, enabling the long-term sharing of perspectives among multiple stakeholders. An iterative process in which decisions are made, systems are impacted, and MM are consciously updated to reflect new perceptions of reality can help develop more sustainable systems (Levy *et al.*, 2018; Moon *et al.*, 2019). In agriculture, when farmers understand how a specific conservation practice or its components fit into the broader agricultural system, this awareness is reflected in their MM. External representations of these assumptions can enable farmers to make more informed decisions about how their agricultural practices might potentially affect social or environmental outcomes (Bardenhagen *et al.*, 2020).

Mental models exert a profound effect on sustainable agricultural practices, including wheat seed use, by shaping how farmers interpret environmental cues, assess risks, and make decisions. For instance, inaccurate or outdated mental models may lead to overconsumption of seeds as a perceived safeguard against risks like drought or weed infestation, resulting in economic inefficiencies and reduced sustainability. Conversely, aligned mental models fostered through education and experience can promote optimal seed usage, enhancing resource efficiency, yield stability, and long-term food security. In this study, differences in mental models between farmers and experts highlight how these cognitive structures directly impact seed consumption behaviors, underscoring the need for interventions that refine farmers' models toward evidence-based practices.

Some research has revealed changes in farmers' MM based on their management styles (Cullen *et al.*, 2022). Related studies by Eckert & Bell (2005) revealed that previous experience, values, beliefs, and knowledge influence a farmer's current MM. In turn, this MM serves as both a filter and guide for farmers' actions, decisions, and use of information, regardless of the type of farming operation, marketing practices, or agricultural approach (e.g. sustainable, organic, or conventional). Warner *et al.* (2016) compared the MM of scientists and local residents regarding flash floods and landslides, demonstrating that personal experience and observability of processes are two key factors explaining the content of MM. In relation to wheat productivity, it can be argued that observable factors such as the average age of the tenant, family labor, distance from home to farm, hired labor, distance from the farm to the irrigation source, number of irrigations, irrigation duration, availability of seeds, and access to and adoption of new, adaptable seed varieties influence the decision-making process. Less observable factors, such as water, fertilizer, and pesticides, may have a lesser impact.

Also a number of studies has begun to explicitly map farmers' mental models concerning specific agricultural inputs, with seeds being a critical focus. Table 1 shows the comparison between previous studies and the present study and identifies its innovation contribution. These studies reveal that seed-related decisions are not purely technical but are deeply embedded in cognitive frameworks shaped by experiential learning, risk perception, and social networks. For instance, Okello *et al*. (2018) applied means-end chain theory to analyze Kenyan farmers' mental models associated with quality seed potato use, revealing that perceived benefits like improved yields and disease resistance drive adoption behaviors. Similarly, Bulte *et al.* (2023) explored biased expectations in Ugandan farmers' mental models regarding improved seeds, showing how misinformation leads to under-adoption and suboptimal complementary input use. These findings underscore the role of mental models in seed-related decisions, aligning with our investigation into discrepancies between farmers' and experts' perceptions of optimal wheat seed quantities.Furthermore, Kansiime *et al*. (2021), highlighted how mental models concerning climate risk directly influence seed selection, with farmers opting for higher seeding rates as a buffer against perceived environmental uncertainties, a finding that resonates directly with the overconsumption problem addressed in the present study. By examining these seed-specific mental models, our study aims to contribute to this emerging body of literature, providing a granular understanding of the cognitive drivers behind wheat seed use in Western Iran.

Table 1- Comparative Analysis of Previous Studies and the Present Research

Aspect	Previous Studies	Present Study	Research Gap Addressed / Contribution
Focus	Often focused on technical aspects of seed use (e.g., purity, germination, varietal selection) or general farm decision-making. Some studies examined mental models in conservation or climate adaptation.	Explicitly focuses on mental models (MM) related to wheat seed consumption specifically overuse in a specific agro-economic context.	Addresses the cognitive and behavioral drivers behind seed overuse, a topic less explored compared to technical or agronomic factors.
Geographical Context	Diverse contexts: Sub-Saharan Africa (Bulte *et al*., 2023), Kenya (Okello *et al*., 2018), Uganda, Europe, and global models (e.g., Levy *et al*., 2018).	Western Iran (Kangavar County), a region with high wheat dependency and specific socio-climatic challenges.	Provides context-specific insights into Iranian farmers' decision-making, where wheat is vital for food security and economy.
Methodology	Varied: interviews (Eckert & Bell, 2005), surveys (Halbrendt *et al*., 2014), behavioral games (Bartaburu et al., 2022), values-informed modeling (Afzal *et al*., 2025), drawing-based methods (Morrison *et al*., 2024).	Mixed-methods: phenomenological interviews, quantitative surveys (t-tests), Delphi method, and Analytic Hierarchy Process (AHP) for strategy prioritization.	Combines qualitative depth with quantitative validation and systematic consensus-building to derive actionable strategies.
Key Factors Explored	Often focused on single domains: risk perception, social norms, or expert-farmer discrepancies. Some studies linked MM to climate or soil management.	Identifies five key MM domains: work context, climate, experienced risks, resources/equipment, and subjective norms. Also compares farmer vs. expert MMs quantitatively.	Offers a multi-dimensional framework that integrates experiential, normative, and contextual factors shaping seed use.
Strategy Development	Few studies progressed to developing and prioritizing actionable interventions based on MM findings.	Uses Delphi and AHP to identify and rank 9 consensus-based strategies (e.g., seedbed preparation, certified seeds).	Bridges the gap between theory and practice by translating MM insights into prioritized, implementable strategies.
Theoretical Integration	Often based on MM theory or behavioral models (e.g., TPB) in isolation.	Integrates Theory of Planned Behavior, Mental Model Theory, and agricultural decision-making frameworks into a unified conceptual model.	Provides a more holistic theoretical basis for understanding seed-use behavior.

Source: Research Findings

Conceptual Framework

Based on the literature, a conceptual framework was developed (see Fig. 1) to illustrate how mental models influence wheat seed consumption among farmers. The framework posits that farmers' mental models are shaped by a combination of experiential factors (e.g., past risks, climate experiences), socio-normative factors (e.g., subjective norms, traditions), and contextual factors (e.g., work conditions, resource availability). These mental models act as cognitive filters that influence farmers' risk perceptions, behavioral intentions, and ultimately, their seed-use practices. This model draws on elements from the Theory of Planned Behavior (Ajzen, 1991), Mental Model Theory (Johnson-Laird, 2010), and agricultural decision-making frameworks (Bartaburu *et al*., 2022; Moon *et al*., 2019).

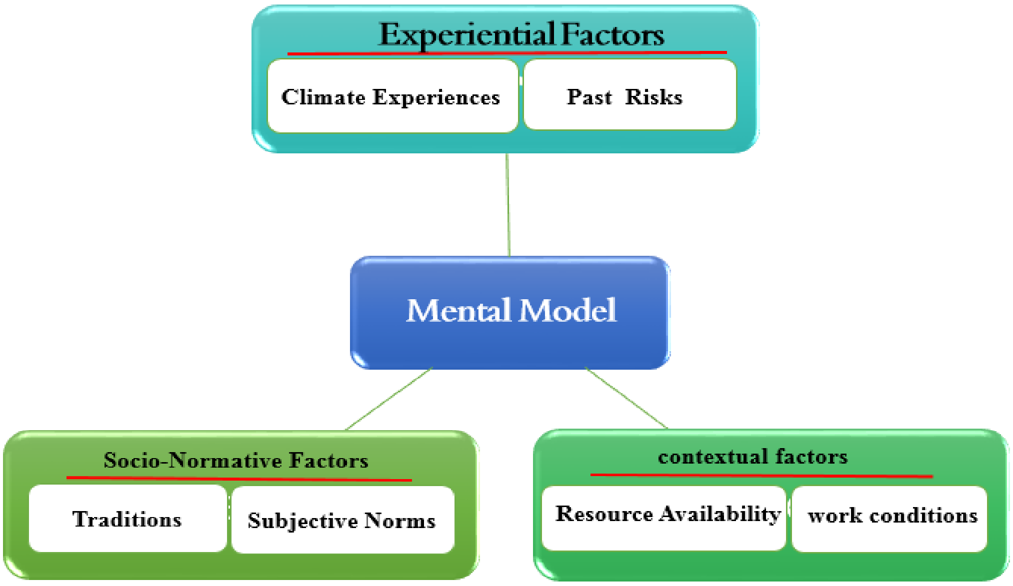

Figure 1- A conceptual model of mental models' influence on seed-consumption

Methodology

This study was conducted in three distinct stages to comprehensively understand and improve the wheat seed consumption practices of farmers in Kangavar County. Kangavar County was selected as a representative case study due to its significant wheat cultivation area and documented issues with seed overconsumption, providing a rich context for examining mental models. The stages included identifying and comparing mental models and developing actionable recommendations.

Stage One: Identifying Mental Models of Farmers and Experts

To elucidate and comprehend the mental models held by wheat farmers and agricultural experts regarding seed consumption practices, a qualitative, phenomenological approach was employed to explore and analyze participants' cognitive frameworks (Creswell, 2013). The study targeted wheat farmers and subject matter experts in Kermanshah County. The inclusion criteria for farmers required a minimum of five years of local wheat cultivation experience. Experts were selected based on a minimum of five years of professional experience in the field (Patton, 2015). Purposeful and snowball sampling techniques were used. The initial participants were selected based on specific criteria, and additional participants were recruited through referrals from these initial contacts (Marshall & Rossman, 2016). The final sample consisted of 16 individuals. We collected data through semi-structured interviews, direct observation, and field notes. These methods were chosen to gain a deep understanding of the participants' cognitive frameworks concerning wheat seed usage (Lincoln & Guba, 2018). The qualitative data were analyzed using a thematic analysis approach. Interview transcripts and field notes were coded inductively to identify significant statements related to seed usage. These codes were grouped into categories and further synthesized into thematic clusters representing key dimensions of farmers' and experts' mental models. This process ensured that the emergent themes were grounded in the participants' lived experiences and perspectives (Braun & Clarke, 2006).

Data were analyzed using Colaizzi's phenomenological method (Colaizzi, 1978), which involves a systematic process of extracting and interpreting participants' lived experiences. The analysis followed these steps:

- ✓ Familiarization: Researchers repeatedly read through all interview transcripts and field notes to gain an in-depth understanding of the data.

- ✓ Identification of Significant Statements: Sentences or phrases directly pertaining to wheat seed usage were extracted from the transcripts.
- ✓ Formulation of Meanings: Researchers interpreted the significant statements to uncover underlying meanings relevant to the research objective.
- ✓ Theme Development: The formulated meanings were grouped into clusters of themes, which were then organized into broader categories.
- ✓ Exhaustive Description: A detailed narrative was constructed to describe the phenomenon of interest comprehensively.
- ✓ Fundamental Structure: The essence of the participants' mental models was synthesized into a concise structural description.
- ✓ Member Checking: The findings were returned to participants for validation to ensure the accuracy and trustworthiness of the interpretations.

Credibility was established through member checking and through peer debriefing. Dependability was ensured by having multiple researchers independently code and review the data (Lincoln & Guba, 2018).

Stage Two: Comparing Mental Models (MM) of Farmers and Experts

To compare and contrast the MM of wheat farmers with those of experts regarding seed consumption. A mixed-methods approach was adopted, integrating qualitative findings from Stage One with quantitative analysis (Creswell, 2013). The population included 255 wheat farmers and 50 agricultural experts from Kangavar County. Stratified sampling with proportional allocation was used for the farmers (N= 740, n= 255) according Krejcie & Morgan (1970) sampling table. Owing to the small number of experts, a complete enumeration approach was applied (Bryman, 2016). A structured questionnaire, developed based on insights from Stage One, was used to assess differences in MM between farmers and experts (Dillman *et al*., 2014).

The structured questionnaire was structured into two main parts. The first part collected socio-demographic information from the participants (e.g., age, education level, farming experience, land size). The second part, which formed the core of the instrument, was designed to quantitatively capture the mental model domains identified in the qualitative stage (Stage One). It consisted of multiple Likert-scale questions (e.g., 1=Strongly Disagree to 5=Strongly Agree) for each domain. For instance, to measure 'Experienced Risks,' participants were asked to rate statements such as, 'Using a higher seed rate is an effective strategy to compensate for potential yield loss due to pests or drought.' Similarly, the 'Subjective Norms' domain included items like, 'Most farmers in my community believe that using more seeds leads to a better harvest.' The 'Academic Knowledge' domain for experts included items such as, 'Recommended seed rates should be primarily based on scientific research from seed institutes.' This approach allowed us to translate the qualitative themes into measurable variables for statistical comparison between the groups .Quantitative data were analyzed using independent samples t-tests to compare the mean scores of farmers and experts across the identified mental model domains. The t-test was chosen to assess the statistical significance of differences between the two groups, with a threshold of $p < 0.05$ indicating significance. This method allowed for a robust comparison of perceptual gaps between farmers and experts. Data analysis involved both descriptive and inferential statistics using the SPSS software (Field, 2013). The differences between the MM of farmers and experts were tested for statistical significance at the 1% and 5% levels.

Stage Three: Developing and Prioritizing Strategies for Optimizing Seed Use

To develop and prioritize strategies aimed at optimizing wheat seed usage among farmers in Kangavar County. This stage employed a mixed-methods approach, utilizing the Delphi method for strategy identification and the

Analytic Hierarchy Process (AHP) for prioritization (Tzeng & Huang, 2011).

Delphi Method: The Delphi process was conducted in three rounds, following the established guidelines outlined by Keeney et al. (2006). A panel of 16 experts participated in an initial open-ended round that generated 21 strategies. In the second round, experts evaluated and prioritized these strategies using a 5-point Likert scale, resulting in a refined list of 14 items. The final consensus round employed binary Agree/Disagree responses, and strategies receiving more than 66% agreement were retained, yielding a final set of 9 strategies.

Round One: An open-ended questionnaire was distributed to a panel of 16 experts to gather potential strategies, resulting in 21 initial strategies (Linstone & Turoff, 2002).

- ✓ **Round Two:** A 5-point Likert scale questionnaire was used to assess and prioritize these strategies, leading to 14 strategies for further evaluation (Keeney et al., 2006).
- ✓ **Round Three:** A closed questionnaire with binary response options (Agree/Disagree) was employed to finalize the top 9 strategies based on expert consensus (Dalkey & Helmer, 1963).

The Delphi technique was employed to achieve expert consensus through iterative rounds of feedback. In the first round, experts generated open-ended suggestions. These were synthesized and rated in the second round using a Likert scale. The final round used binary agree/disagree responses to finalize strategies. This iterative process ensured reliability and collective validation of the strategies (Hsu & Sandford, 2007). The Analytic Hierarchy Process (AHP) was then used to prioritize the strategies based on pairwise comparisons, with consistency ratios maintained below 0.1 to ensure logical consistency.

The Analytic Hierarchy Process was applied to rank the final strategies. Pairwise comparisons were conducted and analyzed using the Expert Choice software. The strategies were ranked based on weighted average scores, with an inconsistency rate maintained below 0.1 to ensure accurate and reliable judgments (Saaty, 1980). The prioritized strategies were designed to optimize wheat seed use, with the potential to improve agricultural practices and enhance the livelihoods of farmers in Kangavar County.

Results

To achieve the research objectives, the researcher aimed to extract the underlying mental frameworks of small-scale farmers regarding seed usage by asking what, how, and why. Data collected from the in-depth interviews and field observations were compiled and organized into a database. Transcriptions and field notes were repeatedly reviewed to gain a comprehensive view of the collected information. Key phrases related to the mental framework of farmers regarding seed consumption were identified, and after eliminating redundant items, 33 key codes (themes) were identified. These were then consolidated into 15 meaningful categories (Table 2). The extracted phrases were grouped into five main thematic clusters: work context, climate, experienced risks, facilities and equipment, and subjective norms.

To identify the underlying reasoning of experts regarding the recommended seed quantity for farmers, key statements related to the research topic (the underlying mental models of farmers concerning wheat seed consumption) were identified after the initial analyses. After eliminating duplicates and merging similar statements, 11 key codes (themes) were identified. The researchers then attempted to consolidate similar items and formulate the extracted statements into meaningful expression. Five formulated meanings were derived at this stage. Subsequently, the statements related to the experts' reasoning regarding recommended seed amounts for farmers were categorized into three main subjects (categories): Academic Knowledge, Professional Experience, and Farmer Characteristics (Table 3).

Table 2- Primary Codes, Concepts, and Categories Extracted from Interviews (Farmers' Mental Models)

Concepts	Categories	Subcategories (Initial Codes)
Work Context	**Soil Structure and Texture**	**Presence of clods in the field**
		Rocky soil
		Heavy soil texture
		Soil fertility
	Land shape	Marginal lands
		Sloped lands
		Irregular land shapes
	Land fragmentation and dispersion	Small plot sizes
		High number of plots
		Inappropriate soil tillage
Climate	Rainfall	Drought
		Decrease in precipitation
		Heavy rainfall
	Air temperature	Cold weather
Experienced Risks	Managing natural risks	Controlling weeds
		Reducing crop pest damage
	Managing financial risks	Preventing yield reduction
		Preventing income loss
Resources and Equipment	Lack of required tools	Lack of tractors
		Lack of proper seed drills
	Inadequate equipment	Use of inappropriate combines
		Use of improper fertilizer spreaders
	Locally made equipment	Inaccuracy of local equipment
	Lack of production inputs	High plowing costs (labor shortages)
		Use of homegrown seeds
		Lack of access to water
		Lack of access to irrigation systems
Subjective Norms	Individual attitudes	Rivalry and competition
	Beliefs and values	Mindset and way of thinking
		Following ancestral traditions

Source: Research Findings

Table 3- Primary codes, concepts, and categories extracted from interviews (Experts' Mental models)

Category	Concept	Theme
Academic knowledge	University resources	Academic textbooks
		Scientific articles
	Information sources	Seed research center
		Scientific and practical standards
		Meteorological center data
Experience	Professional experience	Climatic experience
		Work experience
Farmer characteristics	Personal farmer conditions	Older farmers
		Younger farmers
	Professional farmer conditions	Awareness of farmer conditions
		Type of farmer management

Source: Research Findings

Differences in Mental Models (MM), Between Farmers and Agricultural Promoters and Experts Regarding Seed Usage

An examination was conducted using the t-test to identify differences in MM between farmers and agricultural promoters and experts concerning seed usage. The results showed significant differences at the 1% and 5% levels in the context of working conditions (t = 10.703, Sig. = 0.000), awareness (t = 4.204, Sig. = 0.000), climate (t = 8.184, Sig. = 0.000), experienced risks (t = 17.101, Sig. = 0.000), facilities and equipment (t = 10.615, Sig. = 0.000), and mental norms (t = 12.780, Sig. = 0.000). However, there was no significant difference in the operators' characteristics (t = -0.733, Sig. = 0.464) (Table 4).

To facilitate comparison of the mental

models between farmers and experts, Fig. 2 presents a bar chart illustrating the mean scores for each category, with statistically significant differences (p < 0.01).

Table 4- Comparison of mental models between farmers and agricultural promoters and experts regarding seed usage

Variable	Groups	Mean	Std	t	Sig
Work context	Farmers	65.67	22.325	10.703	0.000
	Experts	35.30	16.764		
Climate	Farmers	48.43	22.314	8.184	0.000
	Experts	20.00	20.763		
Experienced risks	Farmers	74.02	21.542	17.101	0.000
	Experts	15.80	21.768		
Facilities and equipment	Farmers	64.10	19.470	10.615	0.000
	Experts	31.96	18.021		
Subjective norms	Farmers	66.24	19.826	12.780	0.000
	Experts	18.93	24.276		
Academic knowledge	Farmers	41.71	36.239	-8.392	0.000
	Experts	75.28	21.908		
Professional experience	Farmers	66.71	23.784	9.178	0.000
	Experts	22.60	31.852		
Operator characteristics	Farmers	51.51	21.238	-0.733	0.464
	Experts	53.90	18.043		

**Significance at the 1% level is indicated by **

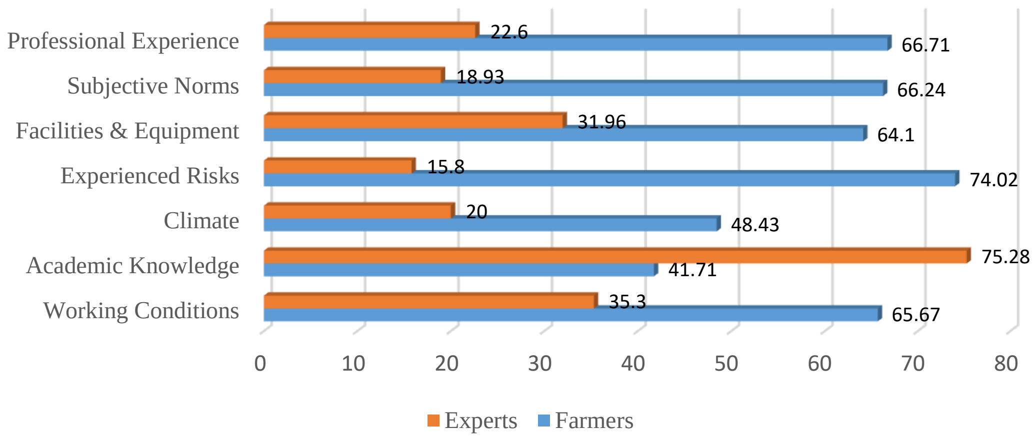

Figure 2- Comparison of mental models between farmers and experts across key categories
Note: ** indicates statistical significance at the 1% level (p < 0.01)

Identifying Strategies to Adjust Wheat Seed Usage among Farmers in Western Iran

The first round of the Delphi method was conducted to identify strategies and suggestions for adjusting seed usage among farmers in Kangavar County, located in western Iran. In this round, 21 strategies were identified and retained. Some of these strategies include preparing a suitable seedbed, plowing before planting (breaking the soil) and leveling the land before planting (frequency of 4), preparing a suitable seedbed (tillage in appropriate moisture, using suitable tillage equipment, managing plant residues) (frequency of 2), increasing beneficial organisms after initial plowing (bacteria that dissolve and provide essential nutrients for the plant in the soil) and restoring soil structure (frequency of 2), replacing old planting equipment with new and modern technology (frequency of 2), and using appropriate seeds (certified and parent seeds) (frequency of 5).

In the second round, items with an average of 3.5 and above were selected, and the others were eliminated. At the end of this stage, seven items were eliminated, and 14 items remained. The remaining strategies at the end of the second stage were preparing a suitable seedbed, plowing before planting (breaking the soil) and leveling the land before planting (average of 5), training farmers on new sciences such as no-till planting or conservation agriculture (average of 4.82), and appropriate depth, density, and uniform distribution of plants per unit area (average of 4.71).

In the third and final round of the Delphi method (consensus phase), items that gained over 66% agreement from experts were accepted, and those that did not reach 66% were eliminated. Ultimately, 5 items were removed, and 9 items were finalized as strategies to adjust seed usage among farmers in Kangavar County, located in western Iran. Some of the selected strategies in this phase included "preparing a suitable seedbed (tillage in appropriate moisture, using suitable tillage equipment, and managing plant residues)" with 93.8% agreement, "using appropriate seeds (certified and parent seeds)" with 87.5% agreement, and "appropriate depth, density, and uniform distribution of plants per unit area" with 81.2% agreement (Table 5).

Table 5- Strategies for adjusting wheat seed usage after third round data analysis

Strategies	Agree (%)	Disagree (%)
Preparing a suitable seedbed (tillage in appropriate moisture, using suitable tillage equipment, managing plant residues)	93.8	6.2
Using appropriate seeds (certified and parent seeds)	87.5	12.5
Appropriate depth, density, and uniform distribution of plants per unit area	81.2	18.8
Planting at the appropriate time and adhering to planting dates	93.8	6.2
Recommending seed rates for each region based on climate, soil, and individual farmer conditions	87.5	12.5
Using suitable planting equipment (calibrated planters equipped with markers)	93.8	6.2
Training farmers in new sciences such as no-till planting or conservation agriculture	81.2	18.8
Encouraging and motivating leading farmers to use less seed and providing incentives for these farmers, creating competition between leading and regular farmers	87.5	12.5
Using treated seeds (soaking seeds in water or spraying zinc compounds on seeds)	93.8	6.2

Source: Research Findings

Prioritization of Strategies to Adjust Wheat Seed Usage among Farmers in Kangavar County, Western Iran

Based on the results presented in Fig. 3, it can be seen that among the identified strategies, the most important and suitable strategies for adjusting seed usage among farmers in western Iran are "preparing a suitable seedbed (tillage in appropriate moisture, using suitable tillage equipment, managing plant residues)" with a weighted average of 0.148, "using appropriate seeds (certified and parent seeds)" with a weighted average of 0.143, and "appropriate depth, density, and uniform distribution of plants per unit area" with a weighted average of 0.131. Strategies with lesser importance included "training farmers in new sciences such as no-till planting or conservation agriculture" with a weighted average of 0.089, "encouraging and motivating leading farmers to use less seed and providing incentives for these farmers, creating competition between leading and regular farmers" with a weighted average of 0.087, and "using treated seeds (soaking seeds in water or spraying zinc compounds on seeds)" with a weighted average of 0.075.

Discussion

Based on the findings, six key categories were identified as influential in shaping farmers' MM regarding wheat seed consumption: working conditions, awareness, climate, experienced risks, facilities and equipment, and mental health norms. The 'working conditions' category, including soil structure, land shape, and fragmentation, shapes mental models through the mechanism of practical constraint and adaptation. Farmers operating on sloped or fragmented lands may perceive a higher risk of uneven plant establishment. This perception, rooted in the affordances of their land, leads to adaptive decisions like increasing seed rates to compensate for perceived inefficiencies, a finding consistent with other studies (Mersha *et al.*, 2022; Feola *et al.*, 2015), and social and physical factors (Xie & Huang, 2021) are significant determinants of farmers' decision-making processes. Peltonen-Sainio *et al.* (2018) further suggested that land shape and slope are hidden factors affecting farmers' decisions.

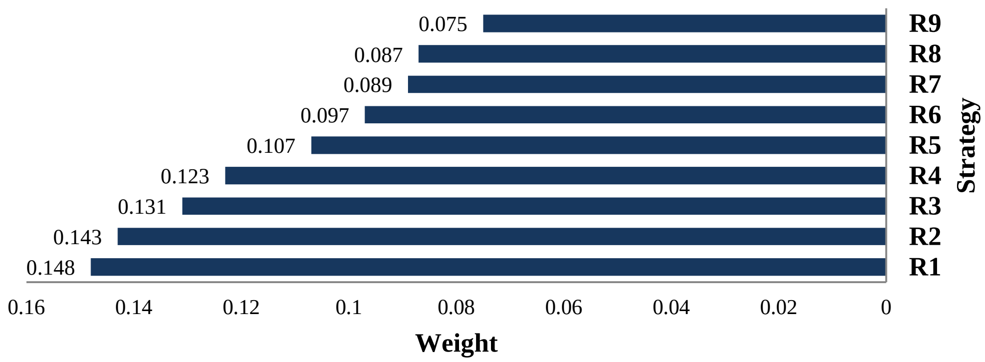

Figure 3- Prioritization of strategies to adjust wheat seed usage Inconsistency rate: 0.07

The findings indicate that climate change is a critical factor influencing farmers' MM of wheat seed consumption. Ellis & Albrecht (2017) also highlighted how climate change intensifies farmers' concerns about weather conditions, weakens their sense of identity, and potentially impacts their mental well-being and subsequent actions. Edwards *et al.* (2015) argue that drought negatively affects farmers' and workers' mental states, especially when drought reduces farm productivity to its lowest levels. Similarly, Gebrehiwot & Veen (2020) add that drought experiences significantly impact farmers' decisions regarding adaptation measures, vulnerability perception, self-efficacy, and the effectiveness of their responses. Harik *et al.* (2023) emphasize the significant role of climate and social factors in influencing farmers' decisions. Azizi *et al.* (2021) also confirm that climate conditions (temperature, rainfall, extreme cold and heat events, and drought) considerably affect farmers' decision-making processes. Based on this, it can be inferred that the farmers studied may have increased their wheat seed consumption owing to the severe drought impacts. In line with this, Taylor *et al.* (1988) confirmed that experiencing climate changes, such as drought, can influence farmers' definitions, memories, and expectations, potentially leading to inadequate responses to environmental risks. Supporting this analysis, Guido *et al.* (2020) found that farmers' expectations regarding future seasonal rainfall play a crucial role in their farm decision-making processes.

The results also revealed that the risks experienced by farmers can shape their MM and ultimately lead to higher wheat seed consumption levels. In this regard, research by Kolb *et al.* (2012), Lemerle *et al.* (2004), and Hasam *et al.* (2021) shows that higher wheat seeding rates (at least 200 plants per square meter) are an effective method for managing weeds, reducing weed biomass, and improving grain yield in low-rainfall environments. Kumari & Kataria (2023) confirmed that a seeding rate of 140 kg/ha in wheat significantly increased both biological and grain yields compared to a rate of 100 kg/ha. Thus, although the farmers studied appear to have shaped their MM based on the risks they have experienced to efficiently manage these risks, their seed consumption rates are well above 140 kg/ha.

The "facilities and equipment" category includes four key concepts: lack of necessary tools, inappropriate tools, and shortages in production inputs, all of which can influence farmers' MM of wheat seed consumption. Feola *et al.* (2015) also confirm that understanding farmer behavior requires addressing decision-making models, short-term pressures, cross-level interactions, and dynamic factors over time.

According to the findings, mental norms (individual attitudes, beliefs, and values) significantly influence the shaping of farmers' MM. In this regard, Ajzen (1991) demonstrated that attitudes and beliefs play crucial roles in forming mental behavior. Ajzen & Fishbein (2000) further noted that attitudes automatically follow accessible beliefs stored in memory and guide relevant behaviors. Highlighting the importance of this factor, Hansson & Kokko (2018) showed that farmers often associate wetland restoration with negative impacts on their fields, with their changing MM influenced by personal values. Additionally, Hoppe *et al.* (2023) found that collective factors, such as in-group identification and norms, directly and indirectly influence individuals' conservation actions. Furthermore, Grob (1995) revealed that personal-philosophical values and emotions have the strongest influence on environmental behavior, explaining 39% of the variance in such behavior. Gatersleben *et al.* (2014) also argue that values and identities are strong predictors of pro-environmental behavior, with identities explaining these behaviors more than specific attitudes.

The analysis showed that experts recommend wheat seed rates based on three main factors: academic knowledge, practical experience, and the farmer's personal and professional characteristics. The academic knowledge category consists of two components—university resources (such as academic books and scientific papers) and informational resources (including seed research centers, scientific and practical standards, and meteorological data).In this regard, Ulrich *et al.* (2022) found that academic education enhances the integration of scientific concepts into experiential brain systems and mental frameworks.

The experience category includes concepts such as climatic and work experience. Rajabali Baglou *et al.* (2019) stated that experience, training, and professional background significantly influence the formation of individuals' MM. Eckert & Bell (2005) also highlighted values and prior knowledge as key factors influencing respondents' mindset and decision-making. According to the findings, from the experts' perspective, the personal and professional traits of the farmer play a determining role in the seed amount they recommend. Therefore, the experts' reasoning and mental frameworks are influenced by these farmer-specific traits.

A comparison of the mental frameworks of experts and farmers revealed a significant difference in reasoning between the two groups, except regarding farmer characteristics. To further elucidate the magnitude of this gap, the percentage difference in mean scores was calculated. The most striking disparity was in 'Experienced Risks,' where farmers' scores were 368% higher than those of experts (74.02 vs. 15.80). Similarly, large differences were observed for 'Subjective Norms' (250% higher for farmers) and 'Facilities and Equipment' (100% higher). In contrast, experts' scores for 'Academic Knowledge' were 80% higher than farmers'. These percentages underscore a profound divergence in perspective. Halbrendt *et al.* (2014) explained that the gap between expert and farmer perspectives can be attributed to the MM each group holds. Our qualitative data provide concrete examples of this divergence. For instance, regarding 'Experienced Risks,' a farmer explained their high seeding rate by stating: "I saw my neighbor's field fail due to poor germination after a dry spell. I always add extra seed as insurance against such losses". This contrasts sharply with an expert's rationale, which was rooted in academic knowledge. *"Our trials show that beyond 150 kg/ha, the law of diminishing returns applies, and excessive seeding can even promote disease"*. Similarly, the influence of Subjective Norms was evident in farmer interviews, with one noting: "*e*veryone in our village plants this much. If I use less and my yield is lower, I will be blamed for not following the tradition”. These examples illustrate how the quantitative disparities are manifestations of deeply rooted cognitive frameworks based on lived experience versus scientific training. Eitzinger *et al.* (2018) argued that these two groups perceive risks differently, which influences their mental behavior. Rios-Gonzalez *et al.* (2013) further noted that this difference in perception arises from the distinct roles of men and women in the agricultural process rather than a lack of knowledgeThe Delphi method was employed to reduce this gap in reasoning and to identify common solutions for optimizing seed consumption. The results indicated that the most effective strategies include: preparing an appropriate seedbed (such as tilling under suitable moisture conditions, using proper tillage implements, and managing crop residues), using high-quality seeds (including parent and certified seeds), and ensuring proper sowing depth, plant density, and uniform seed distribution per unit area. These strategies were identified as the most important and optimal approaches for improving wheat seed consumption among the farmers studied. Less important solutions included educating farmers on new technologies such as no-till farming or conservation agriculture, encouraging and incentivizing leading farmers to use less seed, creating competition between leading and average farmers, and using seed treatments (soaking seeds in water or spraying them with zinc compounds). These solutions were agreed upon by both experts and farmers, aligning with the reasoning of both groups. Therefore, it is expected that by implementing these solutions, wheat seed consumption will significantly decrease.

Conclusion and Limitation

Mental models form the foundation of an individual's decision-making and behavior. By examining reasoning processes, we can identify the root causes of behavioral patterns and avoid unnecessary expenditures of time and resources in altering behaviors. In other words, understanding reasoning enables us to accurately grasp the factors behind farmers' unstable behaviors and implement appropriate solutions to address them. The qualitative and quantitative phases of this study provided an opportunity to explore the reasons for the differences in seed usage logic between farmers and experts. The findings also showed that, through consensus-driven solutions, it is possible to bridge the gap between farmers' and experts' reasoning, thereby creating the conditions necessary to optimize seed consumption.

While this study provides valuable insights into the mental models influencing wheat seed consumption among farmers in Kangavar County, several limitations should be noted to contextualize the findings. Geographically, the research is confined to a specific region in western Iran (Kangavar County). As a case study focused on Kangavar County, the findings are not statistically generalizable to all of Western Iran. The unique climatic, soil, and socio-economic conditions of the region mean that the specific weightings of mental model factors may differ in other areas. For instance, the emphasis on drought-related risks in farmers' mental models may be amplified here due to regional arid conditions, potentially less relevant in wetter climates. Sampling constraints also apply. The qualitative phase relied on purposeful and snowball sampling, which, while effective for in-depth exploration, may introduce selection bias by favoring more accessible or networked participants. The quantitative phase used stratified sampling for farmers (n=255) and complete enumeration for experts (n=50), but the relatively small expert sample size could limit the robustness of comparisons. Additionally, data collection methods, such as interviews and questionnaires, depend on self-reported information, which may be subject to recall bias or social desirability effects. Future research could mitigate these limitations by expanding to multi-regional samples, incorporating longitudinal designs to track changes in mental models over time, or integrating objective measures (e.g., field audits of seed usage) alongside subjective assessments. Despite these constraints, the study's mixed-methods approach offers a solid foundation for understanding farmer-expert discrepancies in this context. Future research could benefit from a longitudinal design and include a more geographically diverse population to enhance the external validity of the findings.

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تأثیر مدل‌های ذهنی بر مصرف پایدار بذر گندم: مطالعه تطبیقی در غرب ایران

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چکیده

درک مدل‌های ذهنی (MM) کشاورزان برای فهم رفتار آن‌ها ضروری است؛ با این حال، این مدل‌ها که از عوامل فنی، اقتصادی و اجتماعی تأثیر می‌پذیرند، اغلب مورد غفلت قرار گرفته‌اند. در پژوهش حاضر سعی شد با استفاده از مطالعه موردی در شهرستان کنگاور (واقع در غرب ایران)، به بررسی مدل‌های ذهنی کشاورزان و کارشناسان در زمینه مصرف بذر گندم در مزارع پرداخته شود و سپس با رویکرد ترکیبی، راهکارهایی برای بهینه‌سازی مصرف آن پیشنهاد شود. در بخش کیفی، به تحلیل پدیدارشناسی تجربیات کشاورزان و کارشناسان در زمینه بذر مصرفی پرداخته شد. مصاحبه با ۱۶ شرکت‌کننده (انتخاب‌شده با نمونه‌گیری هدفمند و گلوله‌برفی) منجر به شناسایی پنج عامل کلیدی شکل‌دهنده مدل‌های ذهنی در کشاورزان (بستر کاری، آب‌وهوا، ریسک‌های تجربه‌شده، منابع در دسترس و هنجارهای ذهنی) و سه مدل ذهنی در کارشناسان (دانش آکادمیک، تجربه حرفه‌ای و ویژگی‌های کاربر) شد. در بخش کمی، پرسشنامه ساختاریافته بر روی نمونه جداگانه‌ای شامل ۲۵۵ کشاورز (نمونه‌گیری طبقه‌ای متناسب) و ۵۰ کارشناس (سرشماری کامل) اجرا شد و اختلافات قابل توجهی را آشکار نمود. آزمون t مستقل، تفاوت‌های آماری معنادار ($p < 0.1$) را در همه حوزه‌های اصلی مدل‌های ذهنی تأیید نمود. پاسخ‌ها ابتدا به‌صورت درصد (۰–۱۰۰) بر اساس میزان توافق با گویه‌ها امتیازدهی و سپس به مقیاس استاندارد ۱۰۰ امتیازی تبدیل شدند. میانگین امتیاز کشاورزان در ریسک‌های تجربه‌شده (۷۴.۰۲ در برابر ۱۵.۸۰)، هنجارهای ذهنی (۶۶.۲۴ در برابر ۱۸.۹۳) و زمینه کاری (۶۵.۶۷ در برابر ۳۵.۳۰) به مراتب بالاتر بود که نشان‌دهنده تأثیر قوی‌تر عوامل تجربی و اجتماعی است. در مقابل، کارشناسان در دانش آکادمیک امتیاز بیشتری کسب کردند (۷۵.۲۸ در برابر ۴۱.۷۱) که بیانگر اتکای بیشتر به شواهد علمی است. روش دلفی، راهکارهای کلیدی را شناسایی و اولویت‌بندی کرد؛ به‌طوری‌که «آماده‌سازی بستر بذر مناسب» (میانگین وزنی: ۰.۱۴۸) و «استفاده از بذرهای گواهی‌شده» (میانگین وزنی: ۰.۱۴۳) در صدر قرار گرفتند. این یافته‌ها بر شکاف عمیق میان مدل‌های ذهنی کشاورزان و کارشناسان تأکید دارند و بر ضرورت مداخلات هدفمند برای پیوند دانش تجربی با شواهد علمی به منظور کاهش این شکاف و ترویج مصرف پایدارتر بذر دلالت می‌کنند.

واژه‌های کلیدی: تولید پایدار گندم، تصمیم‌گیری شناختی، تکنیک دلفی، روش ترکیبی، مدل‌های ذهنی، مطالعه پدیدارشناختی

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Decomposing Total Factor Productivity Growth in Iran's Agriculture Sector with Consideration of Climatic Variables

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Abstract

Climatic conditions are key determinants of agricultural productivity, affecting both production levels and food security. This study aims to decompose total factor productivity growth in Iran’s agricultural sector by explicitly incorporating climatic variables. True Random Parameters Stochastic Production Frontier (TRP-SPF) model and the Maximum Likelihood method were used to estimate parameters in two scenarios, with and without climate variables which are evaluated by TRP_c and TRP_{nc} models, respectively. The results showed that the variables of cultivated area, tractors, and technology have a positive and significant impact on production in both models, and the highest effect observed for cultivated area. In the TRP_c model, the variables of temperature and precipitation also made significant contributions to higher production. The average technical efficiency in the TRP_{nc} model was estimated at 56.5%, and in the model with climatic variables, it decreased to 43.3%. These results confirmed the significant impact of climatic variables on production and suggested that agricultural output could be increased by more than 50% with the same resources and technology, minimizing inefficiency factors and the adverse effects of climatic variables. Decomposition of the Climatic Adjusted Total Factor Productivity (CATFP) index into four components, including climatic effects, scale effects, technical efficiency, and technological progress, revealed that climatic effects have the greatest impact, accounting for 26.4%, while the other three components contributed almost equally to improving productivity. Given the significant impact of climatic variables on agricultural productivity, this study recommends strategies adapting better with climatic conditions of different regions.

Keywords: Agriculture, Climatic effects, Scale effects, Technical efficiency, Total factor productivity

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Introduction

Agriculture is a cornerstone of a nation's economy and a prerequisite for the development of secondary industries. Ensuring stability and prosperity in the agricultural sector is crucial for a country to achieve economic growth and improve living standards. In 2023, the agricultural sector accounted for approximately 4.12% of global GDP. For Iran, this share was 12.8% in the same year, while for some other developing countries, it was reported to be as high as 25% (World Bank, 2024). However, due to the vulnerability of agriculture and its dependence on climatic conditions, agricultural production is significantly influenced by climate change. To sustain dynamism and further development in the agricultural sector, analyzing the impact of climate change on agricultural production has become a critical task for farmers and policymakers alike. In fact, agriculture, as a vital component of the global economy particularly in developing countries faces numerous challenges driven by a variety of factors. One of the most significant of these factors is climate change, which has profound implications for crop production and food security. Over the past few decades, climatic trends in many agricultural regions of the world have been relatively rapid (Lobell & Gourdji, 2012), and climate change is increasingly recognized as the most severe environmental challenge facing humanity. These climatic shifts are expected to continue in the coming decades (Chen *et al*., 2016; Duffy *et al*., 2021). Particularly, changes related to rising temperatures and altered precipitation patterns could lead to significant reductions in agricultural products. Moreover, extreme weather events such as heatwaves and heavy rainfall leading to flooding have been on the rise in recent decades.

According to World Bank data, Fig. 1 and 2 depict the trends in average temperature (in degrees Celsius) and precipitation (in millimeters) for Iran over the past five decades, respectively. A closer inspection of these two critical climatic variables reveals considerable fluctuations throughout the period, suggesting a complex and volatile climate pattern that likely exerts significant pressure on agricultural productivity. While both temperature and precipitation have shown considerable variation, a striking observation is the upward trajectory of average temperature, which has risen from approximately 16°C in 1972 to over 19°C in 2022. This increase in temperature is indicative of a broader global warming trend that may accelerate over time, with potential long-term consequences for agricultural systems, particularly in a region like Iran, where agriculture is highly sensitive to temperature changes. In contrast, precipitation levels have followed a more erratic path. The highest recorded rainfall was 335.79 mm in 1982, whereas the lowest was a dramatic 128.9 mm in 2021. The sharp reduction in precipitation in recent years raises serious concerns, as it signals a potential shift toward more frequent and severe droughts, along with increasingly erratic rainfall patterns. These climatic changes could significantly impact agricultural production and limit the availability of water for irrigation. The combination of rising temperatures and decreasing precipitation over the last five decades poses a significant threat to agricultural production in Iran. The warming climate may increase the frequency and intensity of heatwaves, further stressing crops and reducing yields. At the same time, lower and more erratic rainfall exacerbates water scarcity, making it more difficult for farmers to maintain consistent crop output. Additionally, the variability in these climatic factors introduces a high degree of uncertainty, which can destabilize agricultural planning and long-term sustainability. The interplay between these changing climatic conditions is likely to disrupt traditional farming practices and requires urgent adaptation strategies to safeguard food security and agricultural livelihoods.

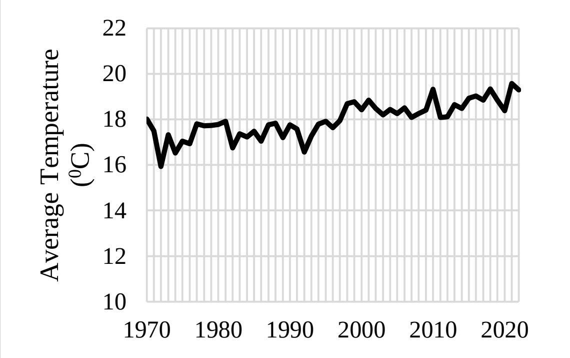

Figure 1- Long-term trend of average temperature

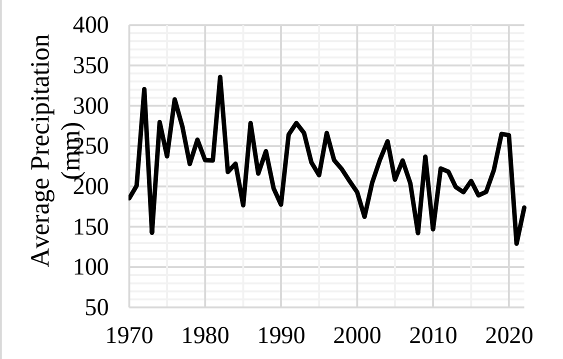

Figure 2- Long-term trend of average precipitation

Increasing agricultural production to meet the growing demands of a rising global population, in the face of climate change threats, remains a formidable challenge (Mall *et al*., 2017). Consequently, climate change particularly temperature and precipitation fluctuations affects the efficiency of agricultural production, which can result in higher food prices and, in addition to impacting food availability, also affects economic access to food (Hosseinzad *et al*., 2023). Furthermore, it can influence the income of agricultural producers (Calzadilla *et al*., 2013). In less developed countries, vulnerability to climate change is more pronounced, exacerbated by low investment in agricultural research (Heisey, 2001). Climate change primarily affects Total Factor Productivity (TFP) in agriculture through two main channels (O'Donnell, 2022). On the one hand, it impacts TFP by altering the availability and allocation of resources, such as changes in rainfall, which serve as additional input variables. On the other hand, it affects TFP by modifying the levels of output variables. It is important to note that the impact of climate change varies across different agricultural regions, as its effects on climatic resources are unique to each specific area. Therefore, measuring the impact of climate change on agricultural productivity is essential for a comprehensive analysis of its effects on agricultural production. According to existing literature, assessments of climate change impacts on agricultural productivity have predominantly focused on very large or small regions and countries. There is a need for further analyses in different parts of the world, such as Iran, to better understand the effects of climatic variables on agricultural production and productivity. This would enable the application of innovative technologies for agricultural adaptation, and the development of effective policies and targeted strategies to address climate change and enhance agricultural resilience. This issue, in addition to improving food security, is critical for guiding farmers in adjusting cropping structures. Awareness of these impacts will significantly influence the experience and outlook of farmers (Rippke *et al*., 2016; Karki *et al*., 2020), and ultimately, global trade will also benefit from a reduction in the impacts of climate change on agricultural production (Njuki *et al*., 2019).

Due to the importance of the topic, various studies have been conducted on the impact of climate change on the agricultural productivity, naturally leading to a comprehensive review by Praveen & Sharma (2019) of reports, articles, and documents evaluating the impacts of climate change on agricultural production. By integrating existing research, they analyzed how climate change influences agriculture, particularly in developing countries, and explored the potential role of agriculture in addressing climate change through sustainable practices. Naturally, researchers, depending on the objectives of their study, utilize different methods to assess the impact of climate variables on productivity. For instance, Liang *et al.* (2017) used a multivariate regression model and estimated that temperature and precipitation factors explained about 70% of the agricultural productivity variation in the United States. Similarly, Ozdemir (2022) analyzed the impacts of climate change on agricultural productivity in the Asia region using autoregressive distributed lag (ARDL) models. Ahmed *et al.* (2023) investigated the effects of temperature increases and political crises on crop yields, focusing on wheat, rice, maize, and soybeans, through simulation analyses. In this study, they identified adaptation measures, such as improved farming practices and technology adoption, as strategies that can enhance productivity. Bouteska *et al.* (2024) employed two modeling approaches, the productivity function and the Ricardian approach, to investigate the impact of climate change on agricultural productivity and food security in Ethiopia. Their findings highlighted the vulnerability of agriculture to climate change and the importance of considering adaptation strategies. It is also important to note that some researchers have used stochastic production frontier (SPF) models and various TFP indexes to analyze the impact of climate variables. For example, Salim & Islam (2010) utilized the Törnqvist index, Sabasi & Shumway (2018) applied the Lowe index, and Njuki *et al.* (2018) employed the multiplicative index. These approaches help in refining the measurement of productivity changes due to climate factors. Moreover, several researchers have conducted predictive studies on the impact of climate change on productivity. In this context, Habib-ur-Rahman *et al.* (2022) predicted the effects of climate change on the yields of rice and wheat, the two main crops in Pakistan. They highlighted that adopting appropriate climate adaptation technologies, such as adjusting planting times and improving irrigation management, could enhance productivity and profitability under changing climate conditions. In line with this, Zhou *et al.* (2024) analyzed the impact of climate change on agricultural total factor productivity in China before making a 30-year prediction, from 2031 to 2060. The study underscores the importance of considering climate change when developing agricultural adaptation strategies.

A review of the studies highlights that all research emphasizes the importance of understanding the impact of climate change on agricultural productivity and food security, and underscores the need for appropriate measures to adapt to climate change, particularly for Asian countries and developing nations. Consequently, the aim of this study is to decompose the growth of total factor productivity in Iran's agriculture sector, with a particular emphasis on climatic variables over the period from 1970 to 2022. This research aims not only to quantify the impact of climate change but also to critically assess the contributions of various factors to the overall productivity growth, providing a comprehensive understanding of the dynamic interplay between climate and agricultural productivity. The methodologies and findings presented in this paper provide a valuable reference for advancing agricultural production under the influence of climate change.

Materials and Methods

TRP-SPF Model

This research applies a True Random Parameters Stochastic Production Frontier (TRP-SPF) approach to model the agricultural production frontier. The TRP-SPF framework is particularly useful for capturing unobserved heterogeneity within the data. It achieves this by introducing observation-specific intercept and slope parameters, which reflect underlying factors such as technological advances, environmental conditions, and variations in input quality that influence agricultural output but are not directly measured in the dataset. These unobserved factors are likely to affect production processes, and the model allows for their implicit inclusion, enhancing the accuracy of the estimated production frontier. In addition to accounting for unobserved heterogeneity, the TRP-SPF model is capable of isolating time-varying technical efficiency, thus providing a dynamic view of how efficiency evolves over time (Greene, 2008). This characteristic is particularly relevant for understanding the long-term agricultural productivity under varying conditions, such as shifts in technology or climate. The model specification adopted here follows a similar structure to the Random Parameter (RP) model, as discussed by Wooldridge (2005), and is conceptually aligned with approaches outlined by Tsionas (2002) and Greene (2008). However, unlike traditional models that analyze cross-country variation, this analysis is confined to a single country. Thus, it focuses on estimating the production frontier within a specific national context, without considering inter-country disparities. The results generated by the TRP-SPF model are then utilized to estimate and decompose Climatic Adjusted Total Factor Productivity (CATFP), offering insights into the productivity changes while adjusting for climatic variations. This decomposition allows for a more refined understanding of productivity growth and its drivers over time. The following TRP-SPF model is employed in this study:

$$y_t = \mu + \sum_{k=1}^{K} B_k x_{kt} + \lambda T + \sum_{j=1}^{J} \eta_j z_{jt} + v_t - u_t \tag{1}$$

where y_t is agricultural production in the t-th time period; x_{kt} is a vector of input variables, which includes factors such as land, labor, machinery, fertilizer, and pesticide; T represents a time trend capturing technological progress over time. It is worth noting that, due to the lack of time-series data on technological progress in the agricultural sector, a time trend variable is used in this study (Ortega & Lederman, 2004; Hosseini & Dashti, 2014; Lachaud & Bravo-Ureta, 2021). z_{jt} denotes a set of climatic variables. μ is a random intercept parameter that accounts for unobserved, time-invariant heterogeneity. B_k is a vector of random slope parameters for the input variables, allowing for variation in how different inputs affect agricultural production across observations. v_t is the error term, assumed to follow a normal distribution with a mean of zero and constant variance. u_t represents a non-negative random term, capturing the inefficiency of agricultural production in time period t, and this inefficiency term follows a half-normal distribution.

The Cobb-Douglas functional form is employed in this study, based on its widespread application in research, as highlighted by Ghoshal & Goswami (2017), Zhang *et al.* (2020), Vasyl'Yeva (2021), Wang *et al.* (2021), and Akbari *et al.* (2022), and due to the consistency of the obtained results with theoretical expectations. Therefore, the empirical model of the present study can be expressed in the form of a Cobb-Douglas specification, as shown in Equation 2. It is worth noting that the labor variable was excluded from the empirical model due to the insignificance of its coefficient.

$$\begin{aligned} \mathrm{Ln}y_t = {} & \mu + \beta_1 \mathrm{LnX}_{\mathrm{lan\,t}} + \beta_2 \mathrm{LnX}_{\mathrm{tra\,t}} + \beta_3 \mathrm{LnX}_{\mathrm{fer\,t}} + \beta_4 \mathrm{LnX}_{\mathrm{pes\,t}} + \\ & \lambda T + \eta_5 \mathrm{LnZ}_{\mathrm{tem\,t}} + \eta_6 \mathrm{LnZ}_{\mathrm{pre\,t}} + \eta_7 \mathrm{LnZ}_{\mathrm{temd\,t}} + \eta_8 \mathrm{LnZ}_{\mathrm{pred\,t}} + v_t - u_t \end{aligned} \tag{2}$$

where, y_t represents the value of agricultural production in thousands of dollars for different years. $\mathrm{X}_{\mathrm{lan\,t}}$ denotes the cultivated land area in thousands of hectares, while $\mathrm{X}_{\mathrm{tra\,t}}$ refers to the number of tractors (machinery) in thousands. $\mathrm{X}_{\mathrm{fer\,t}}$ indicates the amount of chemical fertilizer used, measured in tons, and $\mathrm{X}_{\mathrm{pes\,t}}$ represents the pesticide usage, also in tons. The variable T symbolizes technological progress over time, while $\mathrm{Z}_{\mathrm{tem\,t}}$ refers to the average temperature, measured in degrees Celsius, and $\mathrm{Z}_{\mathrm{pre\,t}}$ denotes the average precipitation, measured in millimeters. The variables $\mathrm{Z}_{\mathrm{temd\,t}}$ and $\mathrm{Z}_{\mathrm{pred\,t}}$ represent deviations of temperature and precipitation, respectively, from their long-term averages to capture climatic variability. Additionally, Ln denotes the natural logarithm.

The model can be estimated by Maximum Likelihood (ML) method, allowing for a robust estimation of the parameters and the calculation of productivity indices. The CATFP index, as described by O'Donnell (2018), is then used to measure and decompose CATFP. The CATFP index for time t relative to a base period s is expressed as Equation 3.

$$CATFPI_{st} = \frac{CATFPI_t}{CATFPI_s} = \frac{Y_t(X_t)}{Y_s(X_s)} \quad (3)$$

where Y_t and X_t represent the aggregate output and aggregate input at time t, respectively. Y_s and X_s represent the aggregate output and aggregate input at the base period s. In the context of this study, the aggregate output Y_t and aggregate input X_t are derived from the results of the TRP-SPF model. These functions are assumed to be non-decreasing, non-negative, and linearly homogeneous. By utilizing the coefficients resulting from the estimation of the TRP-SPF model, the decomposition of CATFP into various components can be expressed as Equation 4 (Lachaud & Bravo-Ureta, 2021).

$$\mathrm{CATFPI}_{st} = \left[\prod_{k=1}^{K}\left(\frac{x_{kt}}{x_{ks}}\right)^{\beta_k - b_k}\right] \times \left[\prod_{j=1}^{J}\left(\frac{z_{jt}}{z_{js}}\right)^{\eta_j}\right] \times \left[\left(\frac{T_t}{T_s}\right)^{\xi} T\right] \times \left[\frac{\exp(-u_t)}{\exp(-u_s)}\right] \quad (4)$$

The components of the productivity function, as represented by Equation (4), are as follows: The first term on the right-hand side of the equation indicates the relative changes in scale effects (SE). The second term reflects the changes in climatic effects (CE), which are influenced by weather conditions. The third term represents the relative change in technological progress (TP). The fourth term captures the relative changes in technical efficiency (TE).

Data

The data used in the present study consists of time series from 1970 to 2022 (53 years) for Iran, including the value of agricultural production in constant 2014 US dollars, cultivated area, number of tractors, labor force, chemical fertilizers, and pesticides. These data were sourced from the FAO website for the study period. It is important to note that the agricultural sector in this research does not include the livestock and poultry subsectors. Additionally, two key climatic variables, precipitation and temperature, were considered, with data for these variables extracted from the World Bank.

Results and Discussion

In this section, initially, the descriptive statistics of the key variables studied in the research, including the mean, minimum, maximum, and standard deviation for all the considered variables, are presented in Table 1. Subsequently, the results obtained from the model estimations will be analyzed.

Table 1- Descriptive statistics (T = 53 years)

Variable	Unit	Mean	Max. (year)	Min. (year)	Standard Deviation
Value of Agricultural Production	Billion USD	20.27	34.57 (2016)	6.51 (1971)	8.64
Land	Million hectares	16.90	18.70 (1995)	13.71 (1980)	1.13
Tractors (Machinery)	1000 No	210.74	352.11 (2022)	20.00 (1970)	107.52
Labor	1000 No	1329.49	4082.6 (2019)	318.14 (1970)	1513.912
Fertilizer	1000 Tone	1608.46	2478.96 (2022)	895.26 (1976)	430.78
Pesticide	1000 Tone	29.52	74.58 (2021)	3.01 (1988)	28.82
Temperature	^{0}C	17.99	19.57 (2021)	15.93 (1972)	0.78
Precipitation	Millimeters	223.45	335.79 (1982)	128.95 (2021)	44.01

Based on Table 1, the value of agricultural production has shown significant fluctuations, with a peak of 34.57 billion USD in 2016 and a low of 6.51 billion USD in 1971. These variations are likely due to factors such as global price changes, domestic agricultural policies, and economic conditions during different periods. The substantial increase in production for recent years, particularly in 2016, may reflect improvements in productivity, technology, or government support. The cultivated land area has also experienced changes, with an average of 16.90 million hectares. The peak of 18.70 million hectares was recorded in 1995, while the lowest value of 13.71 million hectares occurred in 1980. Despite this fluctuation, the overall area has remained relatively stable, indicating structural limitations in agricultural sector. Machinery use (tractors) has grown steadily, with the number of tractors rising from 20,000 in 1970 to 352.11 thousand in 2022. This growth highlights the increasing mechanization of Iranian agriculture, which has become more reliant on technology to boost productivity. This trend suggests the government's focus on mechanization to enhance agricultural efficiency. Labor in agriculture has shown significant variation, with a peak of 4,082.6 thousand workers in 2019 and a low of 318.14 thousand in 1970. These fluctuations may reflect changes in the agricultural labor market, migration, or structural shifts within the sector. The increase in recent years could be related to a rise in agricultural activities or a greater dependence on agricultural employment. Fertilizer use has seen a significant increase over the period, with an average of 1,608.46 thousand tons used annually. The highest use of 2,478.96 thousand tons occurred in 2022, signaling more intensive agricultural practices. However, this also raises concerns about the growing reliance on chemical inputs, which could have long-term environmental implications. Pesticide use has followed a similar pattern, with a sharp rise from 3.01 thousand tons in 1988 to 74.58 thousand tons in 2021. This increase may be driven by higher pest pressures or the expansion of agricultural production, particularly in recent years. Regarding temperature and precipitation, the average temperature during the period was 17.99°C, with a peak of 19.57°C in 2021, reflecting a trend of rising temperatures. Precipitation averaged 223.45 mm annually, with fluctuations throughout the period, including a low of 128.95 mm in 2021. These climatic changes suggest the potential impacts of climate change, which could affect agricultural patterns, water availability, and crop yields. Overall, the data in Table 1 highlights the dynamic nature of Iran's agricultural sector, influenced by changes in production, resource use, and climatic conditions. The observed fluctuations indicate both the challenges and opportunities in adapting to environmental changes, and they underscore the need for effective policy measures to support sustainable agricultural practices and better manage resources in the face of evolving climatic and economic conditions.

In this study, the impact of various factors on agricultural production in Iran is analyzed using the TRP-SPF model, with the results estimated using the Maximum Likelihood Estimation method and reported in Table 2. The model was estimated in two scenarios: one with climatic variables and one without them, to assess the role of climate in shaping agricultural productivity. The factors considered include cultivated area, machinery, chemical fertilizers, pesticides, and climatic variables such as temperature, precipitation, and deviations from long-term averages of temperature and precipitation. The results from both models are compared to better understand the significance of climatic factors in determining agricultural output. Based on this table, the cultivated area is a significant and positive contributor to agricultural output in both models. This indicates that an increase in cultivated area leads to a proportional increase in agricultural production. Specifically, a 1% increase in cultivated area results in an approximate 0.61% increase in production. The inclusion of climatic variables does not significantly alter this relationship, suggesting that increasing the area under cultivation remains a key driver of agricultural production in Iran, regardless of climatic conditions. Machinery has a crucial role in enhancing production. The coefficient for machinery increases from 0.115 (TRP_{nc}) to 0.220 (TRP_c), showing that the effect of machinery becomes even more pronounced when climatic variables are included. The higher coefficient in the model with climatic variables suggests that machinery usage compensates for the negative effects of climate variability, likely by improving efficiency in farming practices. A 1% increase in machinery usage results in approximately a 0.22% increase in agricultural output, reinforcing the importance of technological advancements in boosting agricultural production.

Another point to note regarding Table 2 is that chemical fertilizers (X_{fer}) exhibit a statistically significant impact on agricultural production in the model without climatic variables, but are not statistically significant in the model that includes climatic variables. In the model without climatic variables, the coefficient of chemical fertilizers is negative, indicating that increased use of chemical fertilizers may result in diminishing returns or potentially harmful effects on agricultural output. However, the model with climatic variables suggests that the inclusion of climate factors may alter the relationship between fertilizer use and agricultural production. This indicates that the negative impact of fertilizers may be confounded by climatic variables and may not be as pronounced when the effects of climate are accounted for. It is important to focus on the efficient and sustainable use of fertilizers, particularly in the context of climate variability, to avoid environmental degradation and improve overall agricultural output.

Table 2- Estimates for the TRP-SPF Models without (TRP_{nc}) and with climatic variables (TRP_c)

	Model TRP_{nc}		Model TRP_c	
Variable	**Coefficients**	**t- statistic**	**Coefficients**	**t- statistic**
Constant	1.664	0.70	-5.221*	-1.78
X_{lan}	0.607***	4.28	0.613***	5.40
X_{tra}	0.115***	18.61	0.220***	15.96
X_{fer}	-0.027**	-2.40	-0.032	-1.63
X_{pes}	-0.022***	-5.72	0.031***	4.85
T	0.036**	2.1	0.024***	3.401
Z_{tem}			0.089**	2.37
Z_{pre}			0.331***	2.97
Z_{temd}			0.006	0.65
Z_{pred}			-0.039**	-2.35
σ_u^2	0.162		0.169	
σ_v^2	0.141		0.112	
γ	0.535		0.601	
RTS	0.673		0.864	
TE				
Mean	56.597		43.376	
SD	16.076		11.898	
Min	30.342		25.47	
Max	84.358		68.77	
Log-likelihood	573		693	

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Pesticides have a significant and positive effect on agricultural production, especially in the model with climatic variables. The coefficient for pesticides is negative (-0.022) in the model without climatic variables but turns positive (0.031) in the model with climatic variables. This change suggests that pesticides play a key role in mitigating the adverse effects of environmental factors such as pests and diseases, especially in climates where weather conditions may exacerbate pest problems. A 10% increase in pesticide use leads to a 0.3% increase in production, reflecting the importance of pest control in maintaining agricultural yields. The variable T, representing technology or technological progress, shows a positive and statistically significant effect on agricultural production in both models, indicating that technological advancements contribute positively to agricultural production in both scenarios.

In terms of climatic variables, temperature has a positive and statistically significant effect on agricultural production, with a coefficient of 0.089, suggesting that warmer temperatures may provide certain advantages, such as extended growing seasons. However, the overall effect is relatively small. Precipitation, on the other hand, has a highly significant and positive effect on agricultural output, with a coefficient of 0.331. This indicates that an increase in rainfall improves agricultural production, as it directly benefits crop growth. This finding aligns with the study by Barikani *et al.* (2024), as their research also identified rainfall as a statistically significant factor with a positive impact on the production of rain-fed wheat in Iran. The deviation of temperature from the long-term average shows a minimal and statistically insignificant impact.

The average technical efficiency (TE) in the model without climatic variables is 56.6%, with a standard deviation of 16.1%. In the model with climatic variables, the average TE drops to 43.4%, with a standard deviation of 11.9%. The results suggest significant variation in technical efficiency across the two models. In the model TRP_{nc}, the technical efficiency shows a relatively wide range, with the minimum and maximum TE values being 30.3% and 84.35%, respectively. This indicates that, in the absence of climate factors, the technical efficiency varies substantially, with some regions or periods achieving relatively high efficiency in utilizing inputs. In contrast, in the model that includes climatic variables, the minimum and maximum TE values narrow, ranging from 25.4% to 68.7%. The inclusion of climatic factors appears to reduce the overall efficiency, as evidenced by the lower range of TE. This suggests that climatic factors might introduce additional challenges that negatively affect agricultural production, leading to a decrease in the sector's efficiency. To better analyze technical efficiency in both scenarios from 1970 to 2022, the results are illustrated in Fig. 3. The inclusion of climatic variables reduces the technical efficiency, highlighting that environmental factors such as temperature and precipitation introduce additional challenges and uncertainties that lower the efficiency of agricultural producers. Furthermore, as shown in Fig. 3, it appears that the gap in technical efficiency between the models with and without climatic variables increases over time, suggesting that the impact of climate variability on technical efficiency becomes more pronounced as time progresses.

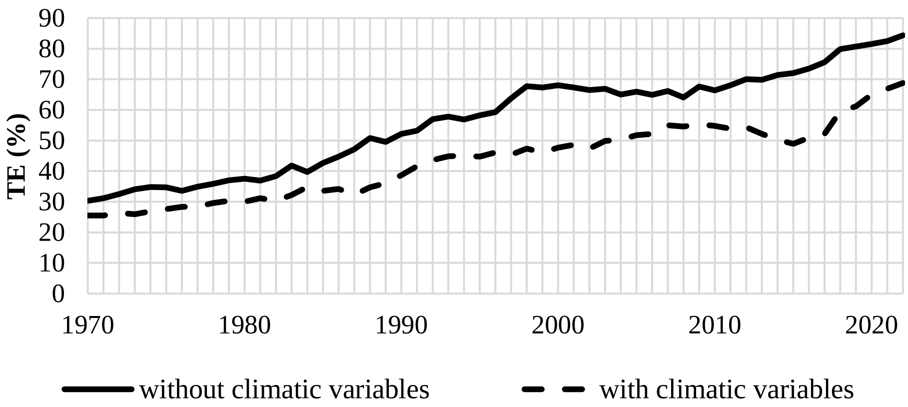

Figure 3- Trends of technical efficiency with and without climatic variables

The results from the TRP-SPF models with and without climatic variables demonstrate that both environmental and non-environmental factors significantly influence technical efficiency in Iran. While factors like cultivated area, machinery, and pesticides continue to show significant positive effects on production, climatic variables introduce substantial risks. Temperature, precipitation, and the deviation of precipitation from the long-term average, significantly affect agricultural output. Temperature shows a slight positive effect, while precipitation has a strong positive influence. However, deviations from normal climatic conditions in precipitation, have a negative impact for production. The reduction in technical efficiency when climatic variables are included highlights the vulnerability of agriculture to climate change. Therefore, agricultural policies must focus on both technological improvements and strategies for adapting to climatic variability to ensure sustainable productivity growth.

Table 3 illustrates the fluctuations in the CATFP index for Iran's agricultural sector from 1970 to 2022, highlighting an overall upward trend. Starting from the base year of 1970, the CATFP reached its highest value of 2.69 in 2022. The average annual growth rate of CATFP during this period was 1.70, indicating that the overall growth rate of agricultural total factor productivity during the study period, compared to the base year, has been 70%. It is important to note that these upward fluctuations are also observed within each decade. For example, by the end of the 1970-1980 decade, Iran had experienced a 7% growth in CATFP compared to 1970. On the other hand, the highest growth in CATFP occurred during the 2010-2020 decade. In addition, the highest fluctuations in the CATFP index occurred during this decade, particularly in the latter half of the decade, ranging from 1.91 in 2015 to approximately 2.4 in 2019, representing a variation of 0.47. Following this, the period from 1990 to 2000 experienced the next largest fluctuations. Overall, while Iran's agricultural productivity has steadily increased over the past five decades, the growth rate was not uniform across all periods. The most substantial advancements occurred in the last two decades, which can be attributed to policy shifts, technological innovation, and improvements in agricultural management. However, challenges related to climate variability and resource limitations can impact the consistency of growth over the years.

The contributions of climate effects, scale effects, technological progress, and technical efficiency to the variability of cumulative CATFP were estimated, and the results are presented in Table 4. According to the findings, the average contribution of climate effects is approximately 26.43%, which is higher than that of other factors. This highlights the significant impact of climatic conditions on the variability of the CATFP index. Following this, technological progress ranks as the second most influential factor, with an average contribution of 24.97%. This indicates that nearly 25% of the variation in the productivity index is attributable to technological progress. Technical efficiency explains 24.55% of CATFP variability, while scale effects contribute the least, accounting for approximately 24% of the productivity variation over the study period.

To provide a more detailed analysis, Fig. 4 illustrates the contributions of these four factors to CATFP from 1970 to 2022. Based on the results in Table 4 and the trends observed in Fig. 4, it can be concluded that scale effects not only had the lowest contribution to CATFP on average during the period under review, but its share in determining agricultural productivity in Iran has also declined over time. In contrast, the contribution of technological progress to CATFP has shown a consistent upward trend. This result is similar to the findings of Lachaud & Bravo-Ureta, (2021).

Table 3- CATFP, average CATFP by decade, and annual growth rate in Iran, 1970–2022

Year	CATFP	Year	CATFP	Year	CATFP	Year	CATFP	Year	CATFP	Year	CATFP
1970**	1.00	1980	1.18	1990	1.51	2000	1.86	2010	2.14	2020	2.55
1971	1.00	1981	1.22	1991	1.63	2001	1.90	2011	2.11	2021	2.62
1972	1.03	1982	1.19	1992	1.71	2002	1.85	2012	2.13	2022	2.69
1973	1.01	1983	1.26	1993	1.76	2003	1.95	2013	2.04		
1974	1.05	1984	1.36	1994	1.76	2004	1.97	2014	1.97		
1975	1.08	1985	1.31	1995	1.75	2005	2.03	2015	1.91		
1976	1.11	1986	1.34	1996	1.80	2006	2.04	2016	1.99		
1977	1.11	1987	1.26	1997	1.78	2007	2.15	2017	2.04		
1978	1.16	1988	1.36	1998	1.85	2008	2.13	2018	2.33		
1979	1.19	1989	1.41	1999	1.80	2009	2.16	2019	2.39		
Average CATFP by decade, and annual growth rate (1970-2022)											
Decade 1970-1980	1.07	1980-1990	1.28	1990-2000	1.73	2000-2010	2.00	2010-2020	2.10	1970-2022	1.70

Note: ** indicates base year. (1970 = 1)

Table 4- Contribution of climate effects, scale effects, technological progress, and technical efficiency in cumulative CATFP

	1970-1980	1980-1990	1990-2000	2000-2010	2010-2020	Average Share
Climatic Effects (CE)	26.97	24.34	26.48	27.39	26.77	26.43
Scale Effects (SE)	25.82	26.62	23.37	22.83	22.64	24.03
Technological Progress (TP)	22.77	24.43	25.71	25.3	26.04	24.97
Technical Efficiency (TE)	24.44	24.61	24.44	24.48	24.55	24.55

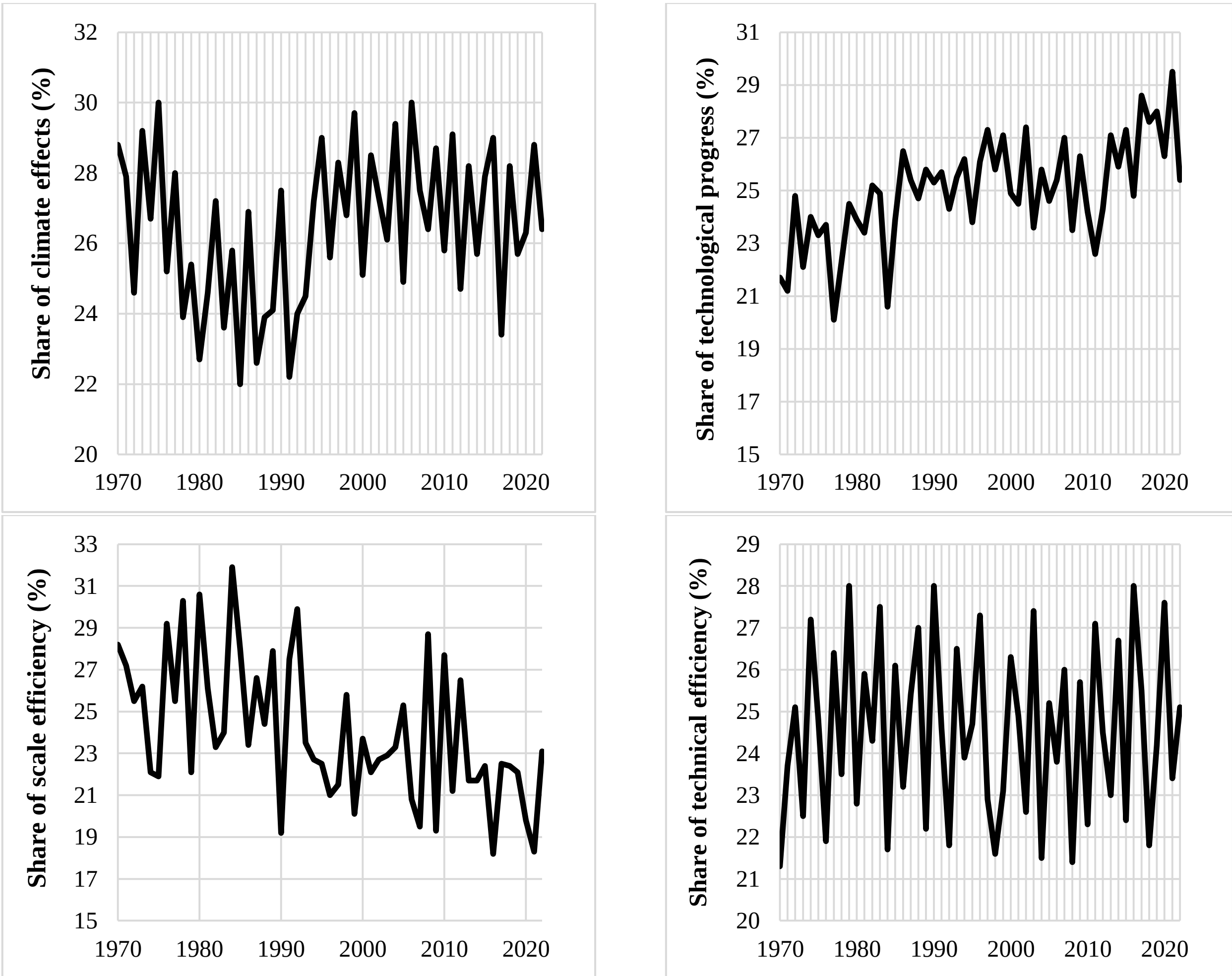

Fig 4- Contribution of technical efficiency, technological progress, scale effects and climate effects in cumulative CATFP

The shares of technical efficiency and climate effects, however, have exhibited fluctuations without a specific pattern over the same period. Notably, the variability of climate effects has been at higher levels in the past two decades.

Conclusion

This study provides an in-depth analysis of the factors influencing agricultural productivity in Iran from 1970 to 2022, with a particular focus on the role of climatic variables. By employing the TRP-SPF model under two scenarios, with and without climatic factors, the findings highlight the critical interplay between environmental conditions and agricultural efficiency. The results underscore several key insights and provide a basis for policy implementation. The findings indicate that increasing cultivated land has consistently contributed to production, but this approach by itself may not deal with meet future challenges. Investment in machinery and advanced farming techniques showed a potential enhancement in output, particularly under conditions of climatic variability. For example, the role of machinery in improving resilience to adverse weather highlights the importance of promoting technological adoption. Climatic factors, while beneficial in optimal conditions, reveal the sector's vulnerability to deviations from historical norms. Temperature and precipitation variability pose substantial risks, with erratic rainfall patterns leading to significant efficiency losses. This underscores the need for targeted adaptation strategies, such as improving irrigation systems and adopting climate-resilient crops. Similarly, inefficiencies in input utilization, such as over-reliance on chemical fertilizers, indicate a pressing need to adopt sustainable farming practices. Addressing these inefficiencies will require both education and incentives to guide farmers toward optimal resource management.

The result showed that the average of CATFP index is 1.7. Despite the general fluctuations in CATFP throughout the study period, the highest fluctuations occurred in the last two decades, which could be attributed to changes and improvements in technology. It is important to note that the contributions of the components of the CATFP have not been constant or uniform over study period. According to the decomposition results of the index into four components, including climatic effects, technical efficiency, scale effects, and technological progress, the contribution of climatic effects has been greater than the other components and has remained at higher levels during the period from 1990 to 2022. It seems that climate change has intensified during this period, a point that is confirmed by many studies. In this regard, according to the results obtained, it was observed that on average, 26.43% of the growth in total factor productivity is attributed to climatic variables. In other words, improvements in precipitation and temperature conditions provide a favorable environment for enhancing productivity, as the high yield of certain modern technologies such as certificated seeds or fertilizers is contingent upon favorable rainfall and temperature conditions. While climatic variables have a prominent effect on productivity growth, the impacts of the other three components, i.e., scale effects and technical efficiency are almost at the same level, with only slight differences. Therefore, in order to improve productivity, considering climatic variables is of significant importance. Replacing more Climate-resilient crops can also contribute to productivity enhancement. In other words, considering weather determinants such as temperature and precipitation, alongside economic factors, will ultimately lead to improved efficiency and increased productivity in the agricultural sector. In addition, given the positive impact of technology and the increasing share of technological progress in productivity growth, the role of modern technology in enhancing the productivity of economic units, especially in agriculture, is undeniable. The use of modern technological practices, such as drip irrigation and certificated seeds, results in higher outputs from a given amount of inputs, which signifies the enhancement and growth of factor productivity

Technical inefficiency is also required to be considered for improving agricultural productivity. In this regard, the technical efficiency of the agricultural sector, even without considering climatic variables, was estimated at approximately 56.6%, indicating the potential for at least a 40% increase in production with the same available resources and inputs. The observed decrease in technical efficiency when accounting for climatic variables suggests that environmental uncertainties hinder optimal resource utilization. Increasing the efficiency of producers by identifying and eliminating the factors causing inefficiency should also be a priority for policymakers in the agricultural sector. Improving efficiency essentially means increasing production with the same resources and technology in order to achieve higher output without incurring additional costs, thus enhancing profitability and the productivity.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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تجزیه رشد بهره‌وری کل عوامل تولید بخش کشاورزی ایران با تأکید بر متغیرهای آب و هوایی

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چکیده

شرایط اقلیمی از عوامل تعیین‌کننده بهره‌وری تولید محصولات کشاورزی است که ضمن تأثیر بر سطح تولید، بر امنیت غذایی نیز مؤثر می‌باشد. بنابراین هدف مطالعه حاضر تجزیه رشد بهره‌وری کل عوامل تولید بخش کشاورزی در ایران با لحاظ متغیرهای آب و هوایی است. برای این منظور، از مدل TRP-SPF و روش حداکثر درست‌نمایی برای برآورد پارامترها در دو سناریو با لحاظ متغیرهای آب و هوایی (TRP_c) و بدون آن (TRP_{nc}) بهره گرفته شد. نتایج نشان می‌دهند که در هر دو مدل، متغیرهای سطح زیرکشت، تراکتور و فناوری تأثیر مثبت و معناداری بر تولید دارند که بیشترین تأثیر مربوط به متغیر سطح زیرکشت است. همچنین در مدل TRP_c، متغیرهای دما و بارش نیز به‌طور معناداری اثر مثبت بر تولید دارند. میانگین کارایی فنی در مدل TRP_{nc} برابر با ۵۶/۵ درصد برآورد شد و در مدل با متغیرهای اقلیمی به ۴۳/۳ درصد کاهش یافت که ضمن تأیید تأثیر قابل‌توجه متغیرهای اقلیمی بر تولید، موید امکان افزایش تولیدات بخش کشاورزی با همان منابع و تکنولوژی به میزان بالغ بر ۵۰ درصد می‌باشد، درصورتی‌که عوامل عدم کارایی و تأثیر سوء متغیرهای اقلیمی به کمترین مقدار خود تقلیل داده شوند. تجزیه شاخص CATFP به چهار جزء، اثرات اقلیمی، اثرات مقیاس، کارایی فنی و پیشرفت فناوری، نشان داد که اثرات اقلیمی با سهم ۲۶/۴ درصدی بیشترین تاثیر و سه جزء دیگر سهم تقریبا یکسانی در ارتقای بهره‌وری عوامل تولید داشته‌اند. نظر به تأثیر قابل توجه متغیرهای آب و هوایی بر عملکرد بخش کشاورزی، اتخاذ تدابیری که انطباق بیشتری با شرایط اقلیمی مناطق مختلف داشته باشد، توصیه می‌گردد.

واژه‌های کلیدی: بهره‌وری کل عوامل تولید، تأثیرات آب و هوایی، کارایی فنی، کارایی مقیاس، کشاورزی

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Factors Contributing to Rangeland Degradation in East Azerbaijan, Iran: Experts' Perspectives

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Abstract

Livestock grazing pressure in East Azerbaijan province, located in the northwest of Iran, is 2.5 times higher than the capacity of rangelands. This study employed a two-stage Delphi technique to identify and rank supervisory, natural, economic, cultural, legal, administrative, and infrastructure factors. The second Delphi round results indicated that, from the experts' point of view, poverty among rural residents on the outskirts of rangelands (scoring 4.7), insufficient support of the *Agriculture Organization* in providing livestock feed and allocation of loans to livestock farmers (scoring 4.53), conversion of rangelands into agricultural and horticultural lands to gain higher profits (scoring 4.43), overgrazing and long term grazing (scoring 4.4), were the important factors contributing to rangeland degradation. Comprehensive legal, legislative, executive, and monitoring measures to prevent overgrazing and premature grazing were identified as key solutions to reduce rangeland degradation. Among economic factors, poverty among rural residents on the outskirts of rangelands and their livelihood dependence on rangelands were recognized as the most significant factors in the destruction of rangelands and forests. Additionally, collaboration with the *Agriculture Organization* in providing alternative forage for livestock, strengthening the monitoring mechanisms of relevant organizations, and enhancing education and awareness levels among the public, regarding the protection of natural resources have been highlighted as other important strategies in reducing the level of rangeland degradation.

Keywords: Delphi technique, Overgrazing, Rangeland degradation, Sustainable land management

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Introduction

Although rangeland degradation is not limited to Iran, environmental data indicate that rangelands are declining in most parts of the country. The total rangeland area in Iran decreased from 84.8 million hectares in 2011 to 83.3 million hectares in 2021. Out of this total, only 6.5% is classified as good condition rangeland, 68.4% as poor, and 25.1% as moderate. According to the reported data, the share of good, moderate, and poor rangelands from the total rangeland area in 2011 was 8.5%, 25.2%, and 66.3%, respectively (Ministry of Agriculture-Jahad, 2022). Although Iran's rangelands are similar to rangelands worldwide, they also have distinct characteristics that require adjustments to traditional management practices. Scholars have identified various factors contributing to the growing trend of rangeland degradation, including natural and human factors (Ansari *et al.*, 2009; Saeedi Geraghani *et al.*, 2014; Zohdi *et al.*, 2004). The current policy framework for agroecological zones lacks robust evaluations of grassland degradation's impact on livelihoods. Adoption of sustainable land management is hampered by a lack of knowledge and experience (Flintan *et al.*, 2011). This deterioration is attributed to a combination of factors, including overgrazing, climate change, and unsustainable land-use practices. Livestock grazing, which is a primary livelihood for many rural communities, often exceeds the rangelands' capacity, leading to soil erosion and loss of vegetation cover. Identifying these factors can be necessary for developing appropriate policies to preserve rangelands and prevent their degradation.

The rangelands in East Azerbaijan Province, located in the northwest of Iran, represent approximately 2.8% of the country's total rangeland area. Despite their relatively small share in terms of land coverage, these rangelands play a disproportionately significant role in the nation's forage production, contributing 5.4% of the total dry forage output. This remarkable productivity highlights the high ecological and economic potential of the province's rangelands, which serve as vital resources for livestock grazing and rural livelihoods. However, the current level of forage production supports a carrying capacity of about 1,561,600 livestock units. Alarmingly, the actual number of livestock grazing in the region far exceeds this figure, exerting a grazing pressure that is approximately 2.5 times higher than the sustainable capacity of the land (Agriculture-Jihad Organization of East Azerbaijan Province, 2022). This overgrazing leads to serious ecological consequences, including soil erosion, loss of vegetation cover, reduced biodiversity, and long-term land degradation. Given the critical role of rangelands in supporting both ecological balance and rural economies, it is imperative to identify the underlying causes of their degradation. Understanding these factors is essential for the development of targeted, evidence-based policies aimed at conserving rangeland resources and promoting sustainable management practices. In this context, the present research seeks to explore and analyze the key drivers of rangeland degradation in East Azerbaijan Province. To achieve this, the study employs the Delphi method, a structured expert-based approach designed to gather, refine, and prioritize expert opinions through multiple rounds of consultation. The findings are expected to provide valuable insights for decision-makers and contribute to the formulation of effective strategies to reduce grazing pressure and preserve the long-term health of the province's rangelands.

Numerous studies have extensively examined the multifaceted phenomenon of rangeland degradation, emphasizing a wide array of contributing factors. Several researchers have highlighted the role of rangeland management practices, such as overgrazing, mismanagement of grazing schedules, and insufficient rehabilitation efforts, as critical drivers of degradation (Ghasemi *et al.*, 2016; Fenetahun *et al.*, 2018; Gokkus, 2020). In addition to technical and managerial aspects, a growing body of literature has emphasized the livelihood strategies of livestock-dependent communities as a major contributing factor. These studies suggest that socioeconomic vulnerabilities, dependence on natural resources for income, and limited livelihood diversification significantly influence rangeland conditions (Amiri Lemar, 2012; Ansari *et al.*, 2009; Ghasemi *et al.*, 2016; Gheitury *et al.*, 2007; Gholampour *et al.*, 2012; Sharifiyan *et al.*, 2014; Belay *et al.*, 2014; Amare, 2015; Gokkus, 2020). Furthermore, social, cultural, and economic dimensions, including land tenure systems, traditional grazing rights, population pressure, and market dynamics, have been recognized as pivotal in shaping the intensity and trajectory of rangeland degradation (Fenetahun *et al.*, 2018; Malekmohamadi *et al.*, 2021; Moyo *et al.*, 2013; Saberi, 2021; Daba & Mammo, 2024). The influence of legal and institutional frameworks has also been acknowledged, particularly in relation to the enforcement of rangeland management policies and property rights, where the absence of coherent legislation or weak implementation mechanisms exacerbates degradation risks (Han *et al.*, 2008; Gheitury *et al.*, 2007; Daba & Mammo, 2024). Lastly, the role of natural and climatic variables, including precipitation variability, soil erosion, and ecological fragility, has been widely reported as an underlying stressor that interacts with anthropogenic drivers to accelerate land degradation (Aryal *et al.*, 2014; Fenetahun *et al.*, 2018; Malekmohamadi *et al.*, 2021; Mussa *et al.*, 2016). These findings collectively underscore the complex and interlinked nature of rangeland degradation, necessitating integrated and context-specific solutions that consider both human and environmental dimensions. Based on the literature review, no comprehensive study has yet examined rangeland degradation in East Azerbaijan Province, Iran. Therefore, the present study aims to identify and prioritize the key factors contributing to rangeland degradation in this region from the perspectives of experts and experienced specialists, and to propose practical mitigation strategies. By employing expert consensus to systematically assess degradation drivers, this research represents the first comprehensive evaluation of rangeland degradation factors in East Azerbaijan Province, highlighting the study's originality and scientific significance.

Materials and Methods

The total area of rangelands in East Azerbaijan Province is 2,340,200 hectares. According to expert estimates, 36% of the rangelands are classified as good, 49% moderate, and 15% poor. In terms of vegetation cover, the rangelands are divided into three distinct groups: mountain renglands utilized during the warm season, mostly located in highlands and cold regions. Steppe renglands are dispersed in low-lying and warm regions and are utilized during the winter season. Transitional pastures are mainly located around villages and serve as permanent grazing grounds. Data show that approximately 6% of the total rangeland area has been degraded over the last ten years (Ministry of Agriculture-Jahad, 2022). Additionally, there were 340 nomadic villages with a population of 44,640 rangeland owners in the province. In 2022, there were 4,845,654 heads of existing livestock and 1,778,145 heads of authorized livestock (Agriculture-Jihad Organization of East Azerbaijan Province, 2022).

This study employed the Delphi technique, in which experts are referred to as Delphi panel members. A critical aspect of the Delphi method is the identification of qualified experts, as the success of the process largely depends on the careful selection of participants. To ensure methodological validity, experts were selected based on four key criteria: expertise and experience in rangeland management, willingness to participate, sufficient availability of time, and effective communication skills (Ahmadi *et al.*, 2008). A pool of potential candidates was compiled from the Agriculture-Jihad Organization, the Department of Natural

Resources, and the Department of Tribal Affairs in East Azerbaijan Province. Through purposive sampling, 58 key experts with demonstrated competence in rangeland-related issues were identified as Delphi panel members. In support of this sampling method, factors such as years of experience, academic credentials, professional roles, and employment history were taken into account.

Required data were extracted from a researcher-developed questionnaire which consisted of four major sections. In the first, questions were designed to investigate the personal and professional characteristics of experts. The second included closed-ended questions about the most important causes of rangeland degradation. The third section covered indicators of rangeland degradation, and the final section included the reduction and control-based strategies for rangeland degradation from their perspective. The initial questionnaire using the Delphi method aimed to screen the primary factors and reach a consensus among experts regarding the influential factors and necessary strategies for reducing rangeland degradation. The average age of the experts was 45 years, with a minimum and maximum of 27 and 57 years, respectively. Most (67%) had a postgraduate education and an average of 12 years of experience, with a minimum and a maximum of 4 and 34 years, respectively. Moreover, 60 experts (approximately 69%) were engaged in agriculture and livestock farming alongside their main occupation. There were 7 experts involved in cropping, 15 in livestock, and 5 worked in both sectors.

Factors contributing to rangeland degradation were identified through a literature review and preliminary interviews with stakeholders and experts, as detailed later in this section. A total of 46 items were categorized into nine groups, each representing a specific dimension influencing rangeland degradation. These categories included: supervisory (4 items), livestock farming (4 items), cultural and social (8 items), economic (8 items), natural (4 items), supportive (2 items), organizational (5 items), infrastructure (6 items), and legal (5 items) factors. In the Delphi method, a Likert scale was used to assess the perceived importance of each item. The responses from Delphi panel members were analyzed to determine the significance of each factor in contributing to degradation. To evaluate the internal consistency of the questionnaire, Cronbach's alpha coefficient was calculated using SPSS software (Table 1). In all cases, Cronbach's alpha coefficient was above or equal to 0.70, ensuring the reliability of Delphi. After collection, based on Delphi method guidelines data comparison and prioritization were conducted. In the second stage, considering the results from the first stage, the second questionnaire was distributed among the same experts. Responses were then analyzed within the framework of the Delphi method.

Table 1- Cronbach's Alpha coefficient values

Variables	Scale	Item count	Cronbach's Alpha	Reliability level
Rangeland degradation effects	Supervisory factors	4	0.75	Acceptable
	Livestock farming factors	4	0.87	Good
	Cultural-social factors	8	0.72	Acceptable
	Economic factors	8	0.95	Excellent
	Natural factors	4	0.8	Good
	Supportive factors	2	0.97	Excellent
	Administrative factors	5	0.73	Acceptable
	Infrastructure factors	6	0.701	Acceptable
	Legal factors	5	0.81	Good
Degradation indicators	-	24	0.79	Acceptable
Destruction reduction and control strategies	-	16	0.86	Good

Ten steps were utilized to implement the Delphi method.

1-Formation of an execution and supervision team.

2-Selection an expert panel.

3-Preparation of first-round Delphi

questionnaires.
4-Testing the questionnaires for sentence construction accuracy.
5-Transfer the initial questionnaires to the members of the expert panel.
6-Analysis of first-round responses.
7-Preparation and arrangement of second-round questionnaires and their testing.
8-Distributing the second set of questionnaires to the members of the expert panel.
9-Analysis of second-round responses. Steps 7 to 9 are repeated until reliable and appropriate results.
10-Preparation and compilation of a report on the analysis of the team's findings to conclude the conducted method.

Then, interviews were conducted with members of the target community. The interview discussion topics were categorized based on the general classification of influential factors derived from the literature review. After the interviews, some group members mentioned points outside the scope of the findings from the initial stage, prompting the researcher to review additional sources and identify scientific references for these mentioned factors to be used and referenced by experts. The findings of the two initial stages were combined. Two rounds were sufficient due to the strong consensus achieved (Kendall’s W = 0.91 in Table 2). A general categorization, consisting of 9 categories (supervisory factors, livestock farming factors, cultural-social factors, economic factors, natural factors, supportive factors, administrative factors, infrastructure factors, and legal factors), was made of 46 factors. This categorization formed the basis of the Delphi questionnaire.

Kendall's Coefficient of Concordance

Kendall's coefficient of concordance indicates that individuals who have ranked multiple variables based on their importance have utilized similar criteria for judging the importance of each variable and, therefore, agree with each other. It has been used to determine agreement among group members, and measure agreement in several categories related to N objects or individuals. By applying this scale, it is possible to obtain the rank correlation among K sets of ranks. Such a scale is particularly useful in studies related to the validity among judges or achieving desirable consensus for completing Delphi rounds. Kendall's coefficient is calculated by equation (1), (Kendall & Smith, 1939).

$$W=\frac{S}{\frac{1}{12}k^2(N^3-N)} \quad (1)$$

where $S=\sum(R_j-\frac{\sum R_j}{N})^2$ represents the sum of squared deviations from the means, which is the sum of ranks corresponding to a factor, K is the number of sets of ranks (number of judges), and N the number of ranked factors. The value is 1 when there is perfect agreement or complete concordance, and is 0 when there is no agreement or complete discordance. If such a consensus does not exist, a constant value or minimal growth of this coefficient in two consecutive rounds indicates a lack of increase in member agreement, and the survey process should be halted.

Table 2- Interpretation of various values of Kendall's coefficient of concordance

Confidence in the order of factors	Interpretation	The value of W
Nonexistent	Very weak consensus	0.1
Low	Weak consensus	0.3
Average	Moderate consensus	0.5
High	Strong consensus	0.7
Very high	Very strong consensus	0.9

Results

Results of Identifying Factors Influencing Rangeland Degradation

The results from the Delphi technique are presented in Table 3. In the first round of Delphi, the Kendall coefficient was 0.8322. According to the ranking results from the first round of Delphi, experts considered the following factors to have the greatest impact on rangeland degradation: inadequate support by the Agriculture-Jihad Organization in providing forage and allocating loans to livestock farmers, rural poverty and their dependence on rangelands, and long-term grazing. In the second round, panel members were provided with a second questionnaire, but the scores for each factor from the first round were included so that individuals could reconsider their opinions based on their collective views. The results collected in the second round showed an increased Kendall coefficient of 0.91. A coefficient of concordance 0.9 suggested further Delphi rounds may have been unnecessary.

The drivers influencing rangeland degradation were ranked. Factors such as poverty among rural rangeland communities, insufficient support from Agriculture-Jihad Organization in providing forage and allocating loans to livestock farmers, conversion of rangelands into agricultural and horticultural lands for higher profits, early grazing, and long-term grazing are ranked as the first to fifth priorities, respectively, with values of 4.7, 4.53, 4.43, 4/4, and 4.29 according to experts' perspectives on rangeland degradation. These factors fall under the subsets of economic, supportive, and livestock farming factors, suggesting economic, supportive, and livestock farming factors had the greatest impact on rangeland degradation. Those factors with a score above 3 in the second round of Delphi were identified as influential in rangeland degradation (Table 3).

Results of Identifying Indicators of Rangeland Degradation

The average numerical value was used to determine the importance and prioritization of indicators of rangeland degradation from the experts’ perspective. In the first round of the process, the standard deviation and Kendall's coefficient of concordance for identifying indicators of degradation from the experts’ viewpoint were 1.08 and 0.63, respectively. It was therefore necessary to continue the process for another round to minimize differences of opinion between the two stages. In the second stage, the value of Kendall's coefficient was 0.78, indicating strong agreement among experts. From the experts’ perspective, the reduction in vegetation cover, sheet and gully erosion of soil, and reduction in vegetation diversity placed first, second, and third priorities, respectively (Table 4).

Results of Identifying Solutions for Reducing and Controlling Rangeland Degradation

Experts were asked to express their views on the solutions for the reduction and control of degradation. Initially, the Delphi method was used to identify solutions to reduce and control rangeland degradation, resulting in a standard deviation of 0.95 and Kendall's coefficient of concordance of 0.87. To increase expert consensus on control solutions, the second stage of the Delphi method was conducted, resulting in a Kendall coefficient of 0.93 (Table 5).

Discussion and Conclusion

The results of prioritizing the identified factors affecting rangeland degradation indicated that the lack of a proper grazing management system, from the supervisory factors; inadequate support from the Agriculture-Jihad Organization in forage supply and the allocation of loans to livestock farmers, from the supportive factors; negligence towards environmental projects and initiatives in national research projects among, from administrative factors; are identified to be as significant contributors to rangeland degradation in the province. Dehghanian & Sarafraz (1998), Stenborg (2008), Han *et al.* (2008), Saberi (2021), and Daba & Mammo (2024) indicated that the government's neglect of rangelands is one of the most significant causes of rangeland degradation. Proper management of rotational grazing and effective supervision by natural resource agencies and other relevant authorities, along with appropriate administrative practices, are among the main proposed solutions presented by experts.

Table 3- First and second Delphi rounds for identifying factors affecting rangeland degradation

	Factors affecting rangeland degradation	First round		Second round	
		Score	Standard deviation	Score	Standard deviation
Supervisory factors	Inadequate supervision over the entry and exit of tribes to the pastures	3.43	0.86	3.54	0.83
	Lack of sufficient supervision over livestock grazing	3.82	0.8	3.97	0.74
	Inadequate supervision of the entry and exit of local and non-local visitors	2.68	1.04	2.54	0.94
	Poor rangeland enclosure management	3.8	0.86	4.02	0.876
Livestock farming factors	Premature grazing	4.07	0.75	4.4	0.71
	Long-term grazing	4.21	0.67	4.29	0.63
	Excessive grazing pressure	3.54	0.78	3.38	0.71
	A large number of beneficiaries	4	1.04	4.13	0.89
Cultural-Social factors	Lack of training courses on the importance and conservation of rangelands	3.86	0.87	4.2	0.81
	Weak cultural awareness within the community regarding the importance of conserving rangelands	3.96	1.05	4	1
	Inadequate communication by officials regarding the organization of training courses on rangeland conservation	3.61	1.01	3.83	0.9
	Population growth	3.64	1.14	3.4	1.02
	Lack of appropriate advertising to promote rangeland conservation, such as using advertising and promotional materials	3.18	0.89	3.2	0.81
	Ethnic conflicts among stakeholders	2.96	1.15	2.98	1.03
	Insufficient water availability in rangelands and its improper distribution	3.21	1.21	3.3	0.97
	Lack of ownership regarding rangelands	3.46	1.27	3.78	1.25
Economic factors	poverty among rural rangeland communities and their economic dependency on rangeland resources	4.33	0.8	4.7	0.81
	Conversion of rangelands into agricultural and horticultural lands by local people to seek higher profits	4.04	0.87	4.43	0.82
	Harvesting and using shrubs as fuel	3.71	1.03	3.9	0.95
	Budgetary constraints and lack of funding for necessary actions to conserve and restore natural resources	3.54	0.91	3.69	0.93
	Livestock farming as the primary livelihood	3.21	0.86	3.29	0.82
	Lack of investment and economic participation by rangeland beneficiaries	3.46	0.94	3.7	0.91
	Lack of rangeland cooperatives	3.04	0.94	3.15	0.90
	Bush clearing to create a livestock enclosure	2.82	1.2	2.92	1.03
Natural factors	Drought	3.82	1	3.92	0.89
	Wildfire	4.14	1.5	4.16	1.6
	Flood	3.18	1	3.2	1
	Soil erosion	3.79	0.9	3.87	0.92
Supportive factors	Insufficient support from the Agriculture-Jihad Organization in providing livestock feed and allocating loans to livestock farmers	4.43	0.98	4.53	0.95
	Allocation of a low budget by the government, including insufficient funding and limited access to bank credits and facilities, for rangeland conservation	3.29	0.99	3.67	0.91
Administrative (Organizational) factors	Limited use of specialized personnel in administrative and executive bodies	3.64	0.89	3.8	0.74
	Increased pressure from other executive bodies to utilization natural resource lands	3.54	1.02	3.59	0.92
	Neglect of environmental initiatives and projects in national research projects	3.71	0.88	3.83	0.81

	Administrative corruption and bribery by natural resources officials from offenders	2.86	1.33	2.93	1.25
	Weak collaboration between the government (natural resource management and Agriculture-Jihad Organization) and the people	3.43	1.02	3.46	0.78
Infrastructure factors	Road construction	3.25	0.95	3.27	0.85
	Water and gas pipeline installation	2.96	1.09	2.95	0.94
	Development of urban and rural areas	3.29	1.22	3.4	1.13
	Implementation of rural development projects	2.75	1.09	2.86	0.89
	Establishment of power plants	2.32	1.31	2.35	1.21
	Agricultural development through Agriculture-Jihad programs, such as increasing cultivated land area by utilizing rangelands	3.11	1.05	3.17	1.15
Legal factors	Official and legal actions of other institutions, such as conducting military maneuvers	2.32	1.23	2.42	1.06
	Lack of appropriate and timely legal actions in dealing with illegal encroachments	3.39	0.9	3.8	0.87
	Weak performance and prolonged process of law enforcement in pursuing offenders in the field of natural resources	3.95	0.75	4	0.71
	Negligence of local officials in matters related to land-grabbing	3	0.93	2.95	0.85
	Weakness or absence of proper laws for the conservation of rangelands	3.29	1.13	3.76	1.08

Table 4- Indicators of rangeland degradation in the first and second Delphi rounds and their prioritization from the perspective of experts

Row	Indicators of rangeland degradation	First-stage score	Second-stage score	Second-stage standard deviation	Ranking
1	Decrease in percentage of vegetation cover	4.14	4.58	0.55	1
2	Surface and gully erosion of soil	4.14	4.22	0.85	2
3	Reduction in vegetation diversity	4.14	4.2	0.75	3
4	Drying of vegetation cover	3.93	4.12	0.87	4
5	Reduction in dominant and palatable plants	3.93	3.96	0.8	5
6	Decline in the quality of rangeland forage	3.68	3.95	1.05	6
7	Decrease in soil fertility	3.86	3.88	0.89	7
8	The appearance of plant roots	3.75	3.84	1.02	8
9	Weakening of plants	3.46	3.8	0.97	9
10	Long-distance livestock for forage consumption	3.57	3.8	1.12	9
11	Reduction in soil properties	3.82	3.77	0.69	10
12	Litter reduction	3.64	3.76	0.76	11
13	Increase in forage grazing time for livestock	3.5	3.65	1.07	12
14	Reduction in primary plant productivity	3.54	3.63	0.86	13
15	Change in plant composition	3.57	3.55	0.84	14
16	Reduction in shrub size	3.39	3.44	0.88	15
17	Change in soil color	3.07	3.1	1.06	16
18	Reduction in height of shrubs	3	3.04	1.03	17
19	Soil salinization	2.82	2.99	1.11	-
20	Livestock emaciation	2.79	2.81	1.05	-
21	Wool shedding of livestock	2.43	2.58	0.97	-
22	Increased incidence of livestock diseases	2.68	2.55	1.2	-
23	Increase in unwanted and non-palatable plant growth	2.64	2.44	0.99	-
24	Reduction in milk and meat production of livestock	2.36	2.4	0.99	-

Table 5- Strategies for reducing rangeland degradation at the end of the first and second Delphi rounds and their ranking

Strategies for reducing rangeland degradation	First-stage score	Second-stage score	Second-stage standard deviation	Ranking
Prevent early grazing	4.43	4.53	0.68	1
Prevent overgrazing	4.46	4.5	0.5	2
Providing alternative forage sources	3.23	4.43	0.8	3
Proper management and effective monitoring by natural resource agencies and other relevant authorities	4.25	4.34	0.91	4
Educating and raising awareness among the public to prevent rangeland degradation	4.25	4.33	0.69	5
Enforcement of laws prohibiting land and rangeland degradation	4.29	4.32	0.8	6
Enclosure management based on rangeland condition	4.11	4.28	0.67	7
Providing facilities for alternative jobs	4	4.23	0.8	8
Maintaining and improving rangelands	4.11	4.12	0.72	9
Implementation of management programs to reduce the dependence of stakeholders on rangeland	4.07	4.11	0.75	10
Providing low-interest loans to stakeholders for the purchase of surplus forage	3.86	4.1	1.12	11
Proper training and conducting promotional classes	3.96	4.05	0.87	12
Limiting the expansion of agricultural lands	3.82	4	0.93	13
Substituting heavy livestock and reducing surplus light livestock beyond the carrying capacity of the rangeland	3.86	3.92	0.99	14
Substituting fossil fuels with charcoal	3.75	3.76	0.91	15
Implementation of rangeland management plans to engage local communities in preventing rangeland degradation	3.07	3.13	0.88	16

Among the infrastructure factors, the development of urban and rural facilities was given top priority in terms of its impact on degradation. Observations also indicate that the development of urban and rural areas has not been carried out with sufficient care, resulting in the destruction of some portions of rangelands for the sake of development. To better manage rangelands, it is recommended to involve local people, who have a comprehensive understanding of the region, native plant species, and their various needs (water, soil, nutrition, etc.), as well as their times of flowering and pollination, in activities such as rangeland enclosure management and protection of rangelands.

Among the socio-cultural factors, the lack of educational courses on the protection of rangelands was ranked as the most important factor. Therefore, it is recommended that an adequate budget be allocated to relevant organizations for conducting promotional classes aimed at educating beneficiaries and livestock farmers about the culture of protecting rangelands. Additionally, the use of billboards and promotional materials in urban and rural areas, near the edge of the rangelands, utilizing advertising messages with positive concepts related to rangeland conservation, and broadcasting targeted radio and television programs, especially during travel seasons, are all parts of cultural initiatives. If these initiatives are carried out in a specialized and continuous manner, it can be expected that they will have a positive long-term impact on reducing the intensity of rangeland degradation. Sharifian *et al.* (2018) identified the lack of culture regarding the protection of natural resources as one of the most important factors contributing to rangeland degradation. Malekmohammadi *et al.* (2021) also highlighted education and cultural awareness as important solutions and corrective measures in addressing rangeland issues.

Among the legal factors, poor performance and the long and time-consuming process of law enforcement in pursuing offenders in the field of natural resources have been recognized as the most significant factors in range factors degradation. Legal actions against illegal encroachments are not taken promptly or, are not fully implemented. Accordingly, the legal instrument sometimes does not function effectively in Iran. Han *et al.* (2008), Ghaytouri *et al.* (2007), and Gholampour *et al.* (2012) have also identified land use change as influential factors in the destruction of pastures and forests. Moradi *et al.* (2016) stated that the lack of decisive and legal action against offenders and the absence of deterrent punishments are among the main reasons for the failure of rangeland management plans. Mirdilami & Moradi (2018) also evaluated the actions and programs of responsible organizations as ineffective in the rangeland management system.

Among economic factors, poverty among rural residents on the outskirts of rangelands and their livelihood dependence on rangelands were recognized as the most significant factor in the destruction of rangelands and forests. The lack of job diversity in rural areas and the reliance on livestock farming as the main occupation have further tied the inhabitants of these areas to the rangelands. Gheitouri *et al.* (2007), Al-Bakri *et al.* (2001), Gholampour *et al.* (2012), Rouhi *et al.* (2012), Aryal *et al.* (2014), Ghasemi *et al.* (2016), Sharifian *et al.* (2018), Saloupour *et al.* (2018), Farajillahi & Ghasemi Aryan (2020), Saberi (2021), Malekmohammadi *et al.* (2021), and Dada & Mammo (2024) have identified income and livelihood factors as influential factors in the degradation of rangelands. Creating non-agricultural employment opportunities and income diversification can play a crucial role in this regard.

Wildfires were identified as a more significant natural factor in rangeland degradation compared to others in East Azerbaijan province. Increasing public awareness by providing necessary information to those visiting natural areas and issuing necessary warnings could prevent unintentional fires caused by 'carelessness or lack of information. Mussa *et al.* (2016) and Gheitouri *et al.* (2007) both highlighted fire as an influential factor in rangeland degradation. The results also indicate that major factors in rangeland degradation were overgrazing, out-of-season, or premature grazing, largely related to economic, social, and cultural issues within the community since livestock farming is often the sole or primary source of income for many rural households. The increased costs of acquiring animal feed and the associated difficulties in its supply, especially in recent years, have further intensified the pressure on rangelands by livestock farmers for feed provisioning. The findings of Gheitouri *et al.* (2007), Han *et al.* (2008), Ansari *et al.* (2009), Jamshidi & Amini (2013), Fenetahun *et al.* (2018), Gokkush (2020), Farajillahi & Ghasemi Aryan (2020), and Mohammadi *et al.* (2022) support the results of this section of the research. It seems that implementing appropriate mechanisms for livestock feed provision and offering it to livestock farmers at a reasonable price can significantly reduce premature grazing and the excessive grazing pressure in rangelands. Providing alternative fodder is one of the three main strategies proposed by the experts to reduce rangeland degradation. Since a cause of degradation is cutting shrubs and branches for fuel, increasing supervision through increasing environmental monitoring and patrols and providing sufficient facilities and human resources can help prevent further damage to the rangelands of the province. Malekmohammadi *et al.* (2021) have identified strengthening supervisory and executive mechanisms and enhancing monitoring of rangeland as effective measures for improving rangeland management efficiency, as has Gheitouri *et al.* (2007). Ultimately, increasing public awareness and fostering a commitment to protecting national assets and natural resources will undoubtedly have a significant impact.

A further factor contributing to rangeland destruction was the construction of rural roads, water, and power networks, as well as oil and gas pipelines by government agencies. It is suggested that comprehensive studies be conducted in the province regarding ongoing construction projects and future projects, with the presence of civil engineers, infrastructure experts, and rural development specialists. This is to minimize the negative side effects of government plans through a multidimensional approach and sustainable development. In addition to all of the above, implementing short-term, medium-term, and long-term planning for investment in rangeland restoration and rehabilitation by the government is essential to prevent further degradation of the rangelands. Sharifian *et al.* (2018) have also identified the lack of development programs and infrastructure deficiencies as important and influential factors in rangeland degradation.

Based on the perspectives of experts from various relevant organizations in East Azerbaijan province, this study identified a range of different factors as influential variables in rangeland degradation, including supervisory, livestock farming, cultural and social, economic, natural, supportive, administrative and organizational, infrastructural, and legal factors. Among all of them, the shortcomings of the government are evident in various aspects. The government has not been able to have positive activities in this field either from the economic, infrastructural, or even educational aspects. The process of destruction shows itself at a slow but steady pace in rangelands, which emphasizes the lack of priority of natural resources in the government's long-term policies and plans.

Availability of Data: The datasets analyzed during the current study are available from the corresponding author upon reasonable request.

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مقاله پژوهشی

جلد ۳۹، شماره ٤، زمستان ١٤٠٤، ص. ۳۵۸-۳٤٥

شناسایی عوامل مؤثر بر تخریب مراتع از استان آذربایجان شرقی، ایران: از دیدگاه کارشناسان

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چکیده

در استان آذربایجان شرقی با توجه به تعداد دام موجود در عرصه مراتع، فشار چرای دام بیش از ۲/۵ برابر ظرفیت مراتع می‌باشد. شناسایی عوامل مؤثر بر تخریب مراتع می‌تواند به تدوین سیاست‌های مناسب برای کاهش تخریب آن کمک نماید. بدین منظور، در مطالعه حاضر با استفاده از تکنیک دو مرحله‌ایی دلفی اقدام به شناسایی و اولویت‌بندی عوامل نظارتی، طبیعی، اقتصادی، فرهنگی، قانونی، اداری و زیرساختی مؤثر بر تخریب مراتع از دیدگاه کارشناسان سازمان‌های منابع طبیعی، امور عشایر و جهاد کشاورزی استان گردید. یافته‌های مرحله دوم دلفی نشان داد که کارشناسان به‌ترتیب وجود فقر در بین روستائیان حاشیه مراتع (با امتیاز ۴/۷)، حمایت کم جهاد کشاورزی در تأمین علوفه و تخصیص وام برای دامداران (با امتیاز ۴/۵۳)، تبدیل مراتع به زمین‌های زراعی و باغی با هدف کسب سود بیشتر (با امتیاز ۴/۴۳)، چرای زودرس (با امتیاز ۴/۴) و چرای طولانی‌مدت (با امتیاز ۴/۲۹) را به‌عنوان مهم‌ترین عوامل تخریب مراتع شناسایی نمودند. براساس نتایج مطالعه، اقدامات جامع قانونی، اجرایی و نظارتی برای جلوگیری از چرای زودرس و بی‌رویه از مراتع به‌منظور تغذیه دام به‌عنوان راهکار کلیدی برای کاهش و کنترل تخریب مراتع شناخته شد. در میان عوامل اقتصادی، وجود فقر در بین روستانشینان حاشیه مراتع و وابستگی معیشت آنان به مراتع مهم‌ترین عامل تخریب مراتع و جنگل‌ها شناخته شده است. همچنین، همکاری با سازمان جهاد کشاورزی در تأمین علوفه جایگزین برای دام، تقویت سازوکارهای نظارتی سازمان‌های ذیربط و افزایش سطح آموزش و آگاهی عمومی در مورد حفاظت از منابع طبیعی به‌عنوان سایر راهکارهای مهم در کاهش سطح تخریب مراتع مورد تأکید قرار گرفت.

واژه‌های کلیدی: تخریب مرتع، تکنیک دلفی، چرای بیش از حد، مدیریت پایدار زمین

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Presenting a Model for Price Discount Strategy in Perishable Products: A Case Study of Fresh Tomatoes

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Abstract

Agricultural products, are mostly perishable, and ensuring their quality through methods like cold storage or optimal conditions can present significant economic challenges for retailers and small-scale producers. In some cases, these products lose their quality and marketability within a span of less than 24 hours. The main challenge in adopting this strategy is determining the timing and amount of the price discount. To optimize price discounting, four functions need to be estimated: a) a time-dependent quality function, b) a price change function, c) a demand function that is a function of price and quality, and d) an objective function, which is considered here as the retailer's profit function. We employ dynamic pricing models that integrate factors such as quality degradation, inventory levels, and consumer behavior. The research data was collected from three fruit and vegetable stores in Gorgan city. The time period was three months, comprising all working days. Each seller was asked to report the price and quantity of sales on an hourly basis from the beginning to the end of the working day. In this way, about 1000 data were recorded from each store. Tomato was selected as case study due to their widespread consumption, continuous supply, and rapid perishability. The results show that price discounts can significantly enhance profitability while reducing the risk of unsold and wasted products. Specifically, the findings indicate that implementing price discounts every 3 to 4 hours yielded the highest profitability. The average discount is 35%, leading to an 82% increase in gross profit. In contrast, shorter discount intervals (every 1 to 2 hours) with an average discount of 18% improved gross profit by 73%. On the other hand, longer discount intervals (every five to seven hours) with an average discount of 46% resulted in a 66% increase in gross profit. Furthermore, this study further emphasizes how crucial consumer perception is to the effectiveness of dynamic pricing methods. The perception of lower product quality brought on by excessive discounting may have a detrimental effect on long-term store credit and customer trust. Perishable product waste can be reduced through the implementation of price reduction strategies. However, the results indicate that sellers' profits increase in the absence of price reductions. Future research could enhance this framework by incorporating additional factors that influence product quality, such as temperature, humidity, and product variety; examining the effects of consumer price expectations on demand; extending the model to other perishable products, including meat and dairy; and leveraging advanced technologies, such as blockchain and artificial intelligence, to improve dynamic pricing and inventory management.

Keywords: Discounts timing, Dynamic pricing, Quality function, Retail markets, Tomato

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Introduction

Cutting prices has also become a fundamental strategy for modern retailers in their bid to win over customers, boost sales, and gain market competitiveness (Santos & Bacalhau, 2023). For products that are perishable, such as fresh fruits and vegetables, the strategy is even more critical due to their short life, rapid deterioration in quality, and the need to determine prices in a timely manner and control inventory effectively (Wang *et al*., 2022). Unlike non-perishables, perishables cannot be stocked for eternity, and their value is devalued very rapidly with time (Blackburn & Scudder, 2009). Hence, the average retailer will then be forced to rely on dynamic pricing techniques to manage stock, reduce wastage, and maximize returns (Kayikci *et al*., 2022). However, how price discounting is tied to product perceived quality is complex and multifaceted. Whereas discounts can increase demand and stimulate consumption, they would most likely also increase consumers' uncertainty about the quality of products, especially if the magnitude of the discount is intermediate or inopportune (Zheng *et al*., 2022). Unlike non-perishable goods, perishable items cannot be stored indefinitely, and their value rapidly diminishes over time (Blackburn & Scudder, 2009). Consequently, retailers often rely on dynamic pricing strategies to manage inventory, reduce waste, and maximize revenue (Kayikci *et al*., 2022). However, the relationship between price discounts and perceived product quality is complex and multifaceted. While discounts can stimulate demand and encourage purchases, they may also increase consumers' uncertainty about product quality, especially when the discount depth is moderate or poorly timed (Zheng *et al*., 2022).

Consumers are likely to associate deep price cuts with inferior quality, and this adds more ambiguity as well as brand distrust and long-term loyalty loss. This is a very challenging thin line between quality perception and price appeal, especially for retailers who deal in perishable goods where there is high risk and little leeway for mistakes (Zheng *et al*., 2022; Aschemann-Witzel *et al*., 2015).

The importance of effective pricing strategies for perishables is reinforced by the challenges created through quality deterioration and inventory control. Fresh produce such as tomatoes is inherently susceptible to quality deterioration over a period of time and is sensitive to temperature, humidity, handling practices, and storage conditions. Recent studies have shown that efficient temperature management of storage is crucial in maintaining the quality and shelf life of perishable food items (Eze *et al*., 2024).

Retailers need to emphasize effective inventory management to minimize quality deterioration and extend product shelf life. Shelf life—defined as the period during which a perishable product maintains acceptable quality, poses a critical challenge in fresh food supply chains. Recent studies highlight the importance of integrating real-time tracking technologies and predictive analytics to improve shelf-life forecasting and support timely and informed distribution decisions. (Rashvand *et al*., 2025; Mamidala, 2023).

Stores must monitor stock levels closely an d implement practices such as First-Expired-First-Out (FEFO) to sell first the older products before the newer ones. FEFO is highly effective in reducing waste and product quality in the business of perishable items (Reid, 2025).

Moreover, as items approach the end of their life cycle, their perceived value decreases, typically requiring price discounts to generate demand. But price actions must be treated with caution so they do not weaken profit margins and compromise the brand equity. Emerging studies have suggested data-driven dynamic pricing frameworks that optimize markdown strategies for perishable products, balancing sales quantity and profitability (Syed *et al*., 2024). Dynamic pricing approaches are increasingly important for the management of perishable goods in modern retail. Static pricing operates on historic data and restricted information, while dynamic pricing utilizes real-time information, such as shelf life left, stock levels, customer demand, and market conditions, to optimize the best price choices and reduce wastage (Syed *et al.*, 2024; Kayikci *et al*., 2022). This flexibility enables retailers to rapidly respond to shifts in market demand and product availability, enabling real-time price strategy optimization to maximize profitability and reduce wastage (Syed *et al.*, 2024). One of the strongest aspects of dynamic pricing is that it is able to match demand and supply in the best possible manner. In the case of perishables, in which stocks are short and demand is volatile, dynamic pricing minimizes food wastage by selling off excess stock before it goes bad and captures maximum revenue during peak demand. For instance, Kayikci *et al*. (2022) propose a four-step data-driven optimal dynamic bulk fruit pricing policy where real-time IoT sensor data is utilized to reduce food losses in retailers. Along similar lines, Nomura *et al.* (2025) depict the implementation of deep reinforcement learning for computing optimal ordering and pricing policies for perishable inventory so that there is more flexible and intelligent decision-making in extremely volatile retail scenarios. Innovations in data analysis and machine learning further amplified dynamic pricing model feature sets more recently. Retailers nowadays can leverage real-time information from point-of-sale systems, IoT sensors, and customer behavior analytics to make more intelligent and responsive price choices. For example, Wang *et al*. (2024) designed a deep reinforcement learning algorithm that optimizes dynamic prices and inventory management for perishable items with age-dependent probabilistic demand. The study uses evidence from actual sources of information obtained from Gorgan stores in Iran to provide recommendations for retailers who are interested in optimizing price techniques, reducing losses, and enhancing profitability. Previous research highlights the necessity of such techniques in dealing with perishable goods (Salmasnia & Talesh-Kazemi, 2022). This study addresses some primary questions: How do consumer demands for perishable products such as tomatoes respond to price discounts? What is the optimal frequency and amplitude of discounts to minimize waste and achieve maximum profit? How does timeliness of perishability impact price and consumer choices? What is the role of inventory management in making dynamic pricing systems successful for perishables?

Efficient inventory management is crucial as it enables effective monitoring of stock levels and product freshness, enabling timely price adjustment to minimize waste and maximize revenue. By offering solutions to these queries, this study seeks to contribute to the increasing body of literature on dynamic pricing and perishable product management (Zhou *et al*., 2023; Hasiloglu-Ciftciler & Kaya, 2025). The findings are expected to provide operational guidance for retailers so that they can make the best possible price decisions, inventory decisions, and waste reduction decisions (Sasanuma *et al*., 2021; Hua *et al.*, 2021). Finally, this research proves that dynamic pricing can be an effective tool that retailers can use to help mitigate the specific challenges of managing perishable products, resulting in improved profitability and environmentally friendly business practices (Hasiloglu-Ciftciler & Kaya, 2025) waste reduction (Sasanuma *et al*., 2021; Hua *et al.*, 2021). Ultimately, this study demonstrates that dynamic pricing can serve as a powerful tool for retailers to navigate the unique challenges of perishable product management, leading to increased profitability and sustainable business practices (Hasiloglu-Ciftciler & Kaya, 2025).

Methodology

Data Collection

This study collected empirical data from three retail stores in Gorgan, Iran, over a three-month period in autumn 2023. The dataset focuses on tomatoes—a highly perishable product with a limited shelf life—to examine the relationship between pricing strategies, sales patterns, and inventory control. The stores were randomly selected in an effort to provide a good sample of the local retail market, witnessing diverse consumers' behaviors and operating practices (Herbon *et al.*, 2014).

Data obtained included the following key variables. Daily sum of retail purchases: total amount of tomatoes purchased by shops per day, which represents levels of supply.Erasing the first hourly price of each day in each shop to a base level of 100, the remaining hourly prices are expressed as relative percentages from starting price. This approach facilitates standardized comparison of intra-day price variations between stores and periods and controls for the effects of variation in baseline prices, store-level characteristics, and seasonality.

Hourly sales by retailer: Sales per hour of tomatoes reveal demand patterns and consumer purchasing behaviors.

Hourly prices were tracked to obtain dynamic prices caused by price movements over the day resulting from retailers' price dynamics. To control for the effects of seasonal fluctuation, store-specific price strategy, and base price variation, the initial opening price for each store on every day was assigned a base value of 100. All the later prices were then quantified in terms of percentage deviation from the base. This standardization permitted systematic and comparable investigation of price differences across different stores and periods, irrespective of relative price levels or other extraneous factors such as location or season.

This complete dataset enabled us to study how the price movement affects the sales by the hour, how inventory varies during the day, and how these variables interact with the perishability of tomatoes (Yang *et al.*, 2014). Through the analysis of such variables, this research seeks to find optimal pricing policies that maximize profit while minimizing waste (Ferguson & Katzenberg, 2006).

Adding hourly price and sales data is particularly beneficial in that it enables the study to gauge actual consumer response to price variations in near real-time. This level of accuracy is essential to grasping the shape of fresh product management, where slight movements in price or quality can have significant implications for sales (Herbon *et al.*, 2014). In addition, the dataset provides a robust foundation for the development of predictive models that will inform future dynamic pricing actions Liu *et al.* (2023).

Model Development

This study employed a dynamic pricing model specifically designed for perishable products, such as tomatoes. This model integrates the following three key factors:

- Quality degradation: Decline in product quality over time.
- Inventory levels: quantity of products available in the stock.
- Consumer demand: The relationship between price, quality, and purchasing behavior.

The model uses the following key equations.

Quality Index (U(t))

Previous studies have shown that the decline in a quality attribute of agricultural products can be approximated by one of four basic mechanisms:

1- Zero-order reactions with linear kinetics,

2- Michaelis-Menten kinetics,

3- First-order reactions with exponential kinetics, and

4- Autocatalytic reactions with logistic kinetics (Khazaeli *et al.*, 2024).

All four methods require laboratory measurements. Each quality feature should be measured separately. In addition, in marketing, quality is related to the perception of buyers, which does not necessarily correspond to laboratory results. According to the above limitations, in this study, the quality was estimated from the perception of product quality through the behavior of buyers. Since the price discount by the seller is due to the buyers' low of acceptance of the supplied quality and price combination of tomato, it is assumed that the price discount is a substitute for the quality of the product. The lower quality, caused the buyers' lower of acceptance and the greater the motivation for a price higher discount by sellers. The reason for choosing the logit function is the form of the decay function, which in all four kinetic models produces a graph similar to the graph of cumulative distribution models such as the logit model.

So the quality index U(t) measures the perceived quality of the product at time t, with values ranging from zero (lowest quality) to one (highest quality). It is defined as:

$$U(t) = Ln\left(\frac{D}{1-D}\right) = f(time) + \epsilon_u \qquad (1)$$

Where D is the average discount applied to the product. In this function, the decay rate is obtained from the following equation:

$$\frac{dD}{dT} = \beta D(1-D)t > 0$$

Price Change (ΔP(t))

The price change ΔP(t) at time t is modeled as

$$\Delta P(t) = \beta_0 + \beta_1 P_{t-1} + \beta_2 U_t + \beta_3 Q_t + \epsilon_{\Delta p} \qquad (2)$$

Where: P_{t-1} is the price in the previous period, U_t is the quality index at time t, Q_t is the remaining inventory at time t, $\epsilon_{\Delta p}$ the error term (random disturbance) in the price change equation at time t.

This equation captures how prices change over time, based on previous prices, product quality, and inventory levels. Coefficients β_1, β_2, and β_3 quantify the influence of each factor on price changes (Elmaghraby & Keskinocak, 2003).

Demand Function q_t

Consumer demand (t) at time t is modeled as:

$$q_t = \gamma_0 + \gamma_1 P_t + \gamma_2 U_t + \gamma_3 t + \gamma_4 t^2 + \epsilon_q \qquad (3)$$

Where P_t is the current price at time t, U_t is the quality index at time t represents the period, ϵ_{qt} is the error term.

Discounting as a Key Strategy

This equation models consumer demand as a function of the price, quality, and time. The inclusion of a quadratic term t^2 allows for nonlinear effects of time on demand, such as increased purchasing behavior during peak hours or reduced demand as the product approaches the end of its shelf life This approach aligns with the modeling strategies employed by Macías-López *et al.* (2021), who incorporated time-dependent demand functions to account for shelf-life constraints in perishable goods .Discounting is a key strategy in this study, implemented to deplete inventory and maximize profit before product quality significantly deteriorates. Pricing adjustments were made at specific intervals (hourly, every three, five, or seven hours). Each pricing adjustment balances inventory levels, consumer demand, and quality degradation.

Hourly price fluctuations are modeled as a function of price, quality, and remaining inventory. Here, P_0 represents the initial retail price of tomatoes. The sales function q_1 can be calculated using the sales quantity q_1 and the quality function u_1. The remaining product quantity was then determined by subtracting q1 from the total product quantity Q in the first period.

The discount amount arises from price change (ΔP), which is influenced by quality changes (u). This allows for the calculation of the new price point, P_1. The remaining product quantity is re-evaluated for the next period (T_2) using the same approach. This cycle of calculations is repeated to assess the sales and remaining product quantities in subsequent periods.

The iterative process in Fig.1 enables an analysis of pricing strategies and inventory management based on sales performance and product quality adjustments. Subsequently, the discount function estimation examines the impact of discounts on profit and provides insights for optimization.

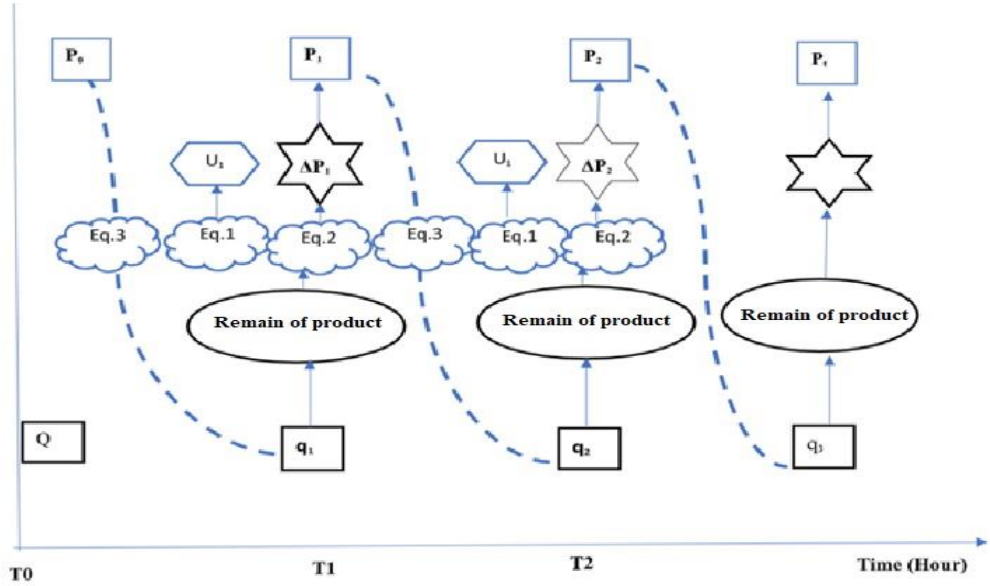

Figure 1- Iterative Discounting Process (research findings)

The dynamic pricing model integrates these equations to optimize the pricing strategies for perishable products. By continuously updating prices based on real-time data, the model aims to:

Maximize profit by adjusting prices to balance demand and inventory levels.

Waste is minimized by ensuring that products are sold before their quality degrades significantly.

Enhance consumer satisfaction: Maintain a balance between price attractiveness and perceived quality (Herbon *et al.*, 2014).

Gross Profit and Net Revenue

$$GP_T = NR_T = \left(\sum_{t=1}^{T} P_t q_t - P_0 \sum_{t=1}^{T} q'_t\right) - C_0 Q \quad (4)$$

Subject to: $\sum_{t=1}^{T} q'_t \leq Q$

In this equation, GPT and NRT represent gross profit and net revenue for a working day (T), respectively. Pt and P0 are the prices in period t and initial price (without discount), respectively. qt and qt′ represent the demand quantities in period t with and without price discounts, respectively. The term inside parentheses represents the difference in gross revenue (sales value) for a working day (T) with and without price discounts. C_0 is the cost of purchasing the product and Q is the total purchase of tomatoes for a working day. This equation is specified considering the inventory constraint. The effectiveness of the model is enhanced by leveraging historical sales and inventory data to inform dynamic pricing decisions in uncertain demand environments (Liu *et al.*, 2023).

Results

Current Pricing Patterns in Retail Stores

Before delving into the model estimations, it is essential to understand the current pricing patterns and sales behavior across the three retail stores. Chart 1 illustrates the average pricing trends for tomatoes over a 16-hour sales period segmented by store. Chart 1 reveals several key patterns.

-Price Decline Over Time: In three stores, prices tend to decrease gradually throughout the day. The highest prices are observed in the early hours (e.g., hours 1 to 6), whereas the lowest prices occur in the final hours (e.g., hours 12 to 16). This trend aligns with the perishable nature of tomatoes, where retailers aim to clear inventory before the end of the day to minimize waste.

-Variability in Pricing Strategies: While the overall trend is similar, there are notable differences in pricing strategies among stores.

For instance, store 3 maintains higher prices in the early hours compared to stores 1 and 2, but it also offers deeper discounts in the midday hours.

Discounts and Sales: Discounts are typically applied during mid-day hours (e.g., hours 7 to 12), but their immediate impact on sales is not always evident. For example, in store 1, the highest discount (27%) was offered at hour 10, but the corresponding sales did not show a significant spike. This finding suggests that customer responses to discounts may be delayed or influenced by other factors.

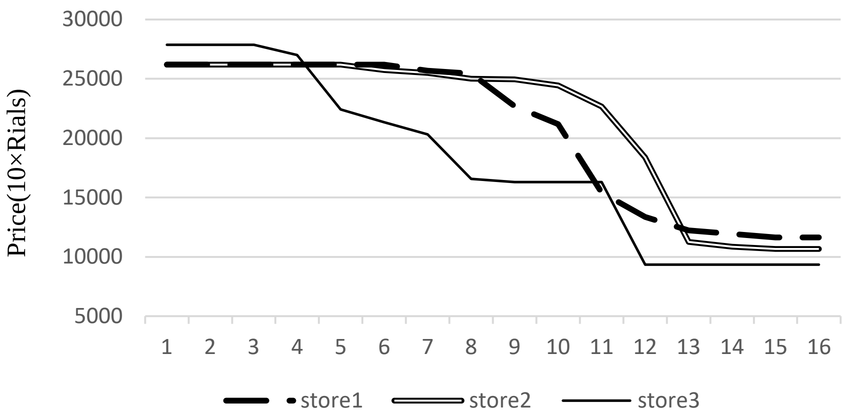

Chart 1- Average Pricing Trends for Tomatoes across Three Retail Stores (Research Findings)

These observations highlight the dynamic nature of pricing in the retail environment and underscore the need for a deeper analysis of the factors that drive price changes and their impact on sales.

Model Estimations

After examining the current pricing patterns, we now discuss the model estimation results. Table 1 summarizes the key findings of the quality, price changes, and demand functions.

Quality Degradation over Time

Chart 2 illustrates the gradual decline in the tomato quality over 24 h. At the beginning of the day, the quality index was high (0.66), indicating fresh, and high-quality tomatoes. However, by the end of the day, the quality index dropped significantly (0.14), emphasizing the importance of timely price adjustments and inventory management to reduce waste and maximize profitability.

The quality equation transforms the average daily discount rate (Δ) into a logarithmic format, enabling the calculation of the probability of a product's quality. The quality index is derived from the discount, where a higher discount is associated with a lower quality index. This ensures that as the discount increases, the perceived quality decreases. The quality function was considered to be dependent on the storage duration of tomatoes, assuming constant environmental conditions. A nonlinear and decreasing relationship between quality and time was obtained. According to the estimation, the effect of each passing hour on the tomato quality depends on the shelf life of the product in the store. Therefore, time has a positive and statistically significant effect on the likelihood of quality degradation. The F-statistic value is 6.73, indicating the overall significance of the model. The RSS was 250, which represented the prediction error of the model.

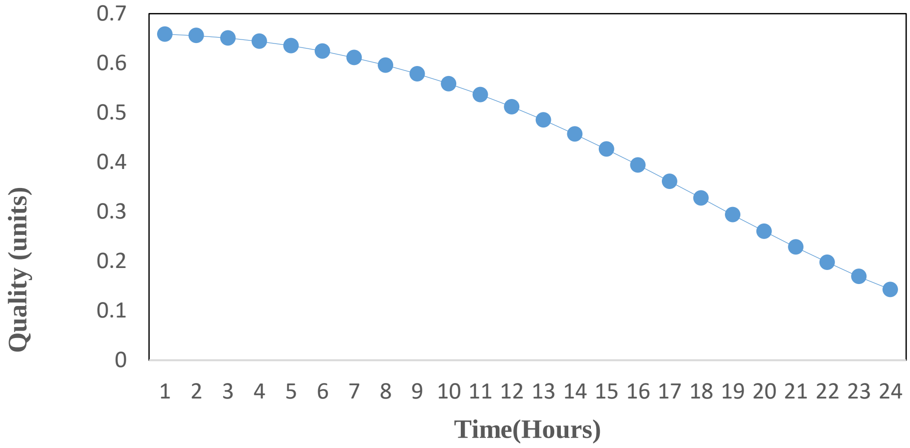

Chart 2- The Relationship between Quality and Time (24 Hours)

Price Change and Demand Dynamics

The price change function (Table 1) shows that previous prices have a negative and statistically significant effect on current price adjustment. This finding suggests that retailers tend to lower prices in response to higher previous prices, which is likely to stimulate demand and clear inventory. The demand function highlights the relationship between price and sales. The coefficient of 0.27 for the price variable indicates that a 1% increase in price leads to a 0.27% decrease in demand, reflecting the price sensitivity of customers. Additionally, the quality variable had a positive and significant impact on demand, with a coefficient of 10.4. This underscores the importance of maintaining product quality in driving sales. The findings from the model estimations align with the pricing patterns observed in retail stores. The gradual decline in prices over the day, coupled with the significant impact of quality on demand, highlights the challenges retailers face when managing perishable products.

Table 1- Model estimations

Dependent Variable / Independent variable	Quality (unit)	Price Change (%)	Demand (%)
Constant	-0.66** (0.14)	129.8** (31.14)	
Time(hour)			0.27** (0.016)
Time^2	0.004** (0.002)		-0.014** (0.001)
Price (-1)		-0.23 (0.02)	
Quality		-77.34* (30.9)	10.4** (0.5)
Non-Sold (%)		-0.59** (0.075)	
Price^{-1}			11.5** (1.56)
F	6.73**	25.6**	53.2**
RSS	250	78937	41.51
Durbin-Watson stat		1.33*	2.38**

Superscripts * and ** denote p<0.05 and p<0.01 respectively
Source: research findings

Although discounts are extensively used in the pursuit of sales, their immediate impact is not always apparent. There may be a need for retailers to pay more attention to the timing and quantity of discounts to maximize their effectiveness. Sharp drops in tomato quality underscore the importance of efficient management of inventories. Retailers should pay attention to strategies that minimize waste, such as dynamic pricing and targeted promotion. Knowing customer price and quality sensitivity is important in determining the best pricing strategy. Retailers can apply data analytics to establish trends in consumer behavior and adjust their pricing strategies in response.

The function for changing price has an intercept (constant) of 129.8, which is the base price when all the variables equal zero. The coefficient for the price of the last period (Price (-1)) is -0.23, meaning that the price change is reduced by a rise in the price of the last period, with a standard error of 0.02. The quality function is -77.34, meaning that the higher the quality, the lower the price changes, with a standard error of 30.9. The coefficient of product not sold (non-sold) is -0.59, indicating
that a rise in product not sold decreases change s in price with a standard error of 0.075. The F-statistic of the model was 25.6, which confirmed the model's significance as a whole, and the Residual Sum of Squares (RSS) was 78,937, which is the prediction error, indicating the explained variation in the dependent variable, which may be due to omitted variables or random shocks. Price does vary over time, calculated from Equation 2, indicating that higher previous prices decrease average discounts and suggesting that more costly tomatoes require lower discounts to sell.

The coefficient of quality index is a measure of a strong negative correlation, where the lower the quality, the higher the discount, in the sense that the more valuable tomatoes are less discounted. The coefficient does not show unsold product, which states that discounts increase as inventory decreases, meaning that discounts are used to accelerate the sales of the remaining amount. The constant term reflects the regular discount when all independent variables are zero. The time coefficient for the demand function is 0.27, which implies that demand increases by 0.27 percent as time elapses, while its standard error is 0.016. The time squared (Time^2) coefficient is -0.014, which reflects a non-linear effect in which the increasing rate in demand declines over time, with a standard error of 0.001. The coefficient on quality is -10.4, meaning that decreasing quality increases demand with a standard error of 0.5. The coefficient for the price in the previous period (Price (-1)) is -0.23, indicating prices in the previous period decrease current demand, with a standard error of 0.02. The negative of the inverse price (Price^{-1}) coefficient is -11.5, showing that higher prices in a year lower demand in the year at hand, with a standard error of 1.56. The F-statistic for the model was 53.2, confirming the model's significance as a whole, and the Residual Sum of Squares (RSS) was 41.51, measuring the error of prediction. Demand, by the sales index (q_t), is estimated by Equation 3, where quality and the previous period's price have positive and significant impacts on demand, and the relationship between time and demand is nonlinear. The designed models reflect the complex interactions among pricing, quality, and demand. The quality index is negatively correlated with discounts, i.e., more quality reduces the need for discounts. The discount function shows how price, quality, and stock levels determine pricing measures to provide d iminishing discounts for increasing prices and quality, and unsold stocks to provide greater discounts to induce sales more quickly. The demand function shows how prices, quality, and time operate together to determine overall sales performance, where demand increases with time but at a declining rate, and higher prices lower current demand. These findings reflect the importance of quality, price, and stock balancing to achieve maximum profitability and sales.

Price Discounts and Profit

It was observed that the price discounts every 3–4 hours earned the highest profit.

Discounts provided at higher intervals (e.g., every 1–2 hours) resulted in rapid price reductions and minimal overall profit since buyers considered the product to be of lesser quality. In the Hourly discount, the price decreases to 95.26 in the second hour and to 60.65 in the third hour. This steep drop represents a rapid loss of product value over short periods (Chart 3).

Average discount stands at 14.83%, and the average discount rate stands at 14.83% per hour. As compared to this, using a discount every two hours demonstrates a lower price reduction. Here, the price goes down to 89.28 in the first period and reaches 61.78 in the third period. The average discount is 20.76%, and the average discount rate is 10.38% per hour. This shows that longer time intervals can reduce the loss of the value. However, discounts taken at longer intervals (e.g., every 5 to 12 hours) yielded fewer sales and more waste, since product quality deteriorates greatly before selling. A discount taken every three hours significantly moderates the price drop. Here, the price drops to 82.39 in the first interval and becomes 44.42% in the third interval. The average discount rate is 31.85% and 10.62% an hour. This indicates that longer periods can handle the loss of value more effectively. Each four-hour discount shows a declining trend. In this, the price drops to 75.80 in the first interval and to 37.15% in the third interval. The mean rate of discount is 37.59% and 9.40% an hour. This clearly shows that larger time intervals can handle the decline in value better. Finally, a discount every five hours shows the highest stability in prices. Here, the price drops to 70.70 for the first interval and to 38.01 for the third interval. The average discount rate is 53.52% and 10.70% hourly. This supported that the longer time intervals worked more efficiently. For discounts every six hours or less frequently, the lowering of the price is much more gradual, and prices are maintained more stable for longer intervals. The research also determined that dynamic pricing methods, which change prices in response to real-time information, outperform static pricing when it comes to profit maximization and waste reduction (Chart 4). The trend for profit uniformly rises in the discount intervals of 1 to 4 hours. For instance, profit increases from 32.70 in hourly discount to 70.84 in 4-hour discount.

This is due to greater customer involvement during these intervals. The growth rate of profit was positive during such time intervals. That is, the difference in profit rate is 5.22 units between the hour and 2-hour discount, 5.70 units between 2-hour and 3-hour discount, and 3.46 units between the 3-hour and 4-hour discount. This indicates that standard short-term discounts can enhance demand and maximize profits.

Profits begin declining after a 4-hour interval. For instance, the profit drops from 70.84 in the discount of 4 hours to 70.76 in the discount of 5 hours. The decline is tremendous: from 4-hour to 5-hour discounts, the profit drops by eight units; from 5-hour to 6-hour discounts, the profit drops by 12.3 units; from 6-hour to 7-hour discounts, the profit drops by 8.82 units; and from 7-hour to 8-hour discounts, the profit drops by 17.8 units. The steepest decline is between 5-hour and 6-hour intervals, indicating that the profit decline accelerates after 5 hours. Between 9 and 12-hour intervals, the rate of profit loss accelerates drastically. This indicates a reduction in demand or the reduced utility of discounts within these hours. This sharp profit decline may be accounted for by the degradation of product quality or declining customer desire for protracted discount provisions. Every discount, every 1 to 4 hours, provides maximum profit and is strongest in that it induces faster sales and maximum profitability. But after the 4-hour mark, profit dips, and it takes strategic considerations such as combining 3-hour and 5-hour discounts to balance losses. In 5- to 8-hour intervals, in which profit loss is large but relatively slower, methods such as raising offer attractiveness or providing additional services (e.g., free packaging) can be applied. In 9-to-12-hour intervals, where profit loss is severe, long-term discounts should be avoided, and other approaches such as bundle sales or companion product promotion are best. Profit reduction steepens to become negative after the 4-hour interval, with precipitous falls at 4-hour and 5-hour discounts (-8 units), 5-hour and 6-hour discounts (-12.3 units), 6-hour and 7-hour discounts (-8.82 units), and 7-hour and 8-hour discounts (-17.8 units). These findings underscore the necessity for adaptively varying discounting practices as a function of customer reaction and product characteristics to achieve optimal profitability.

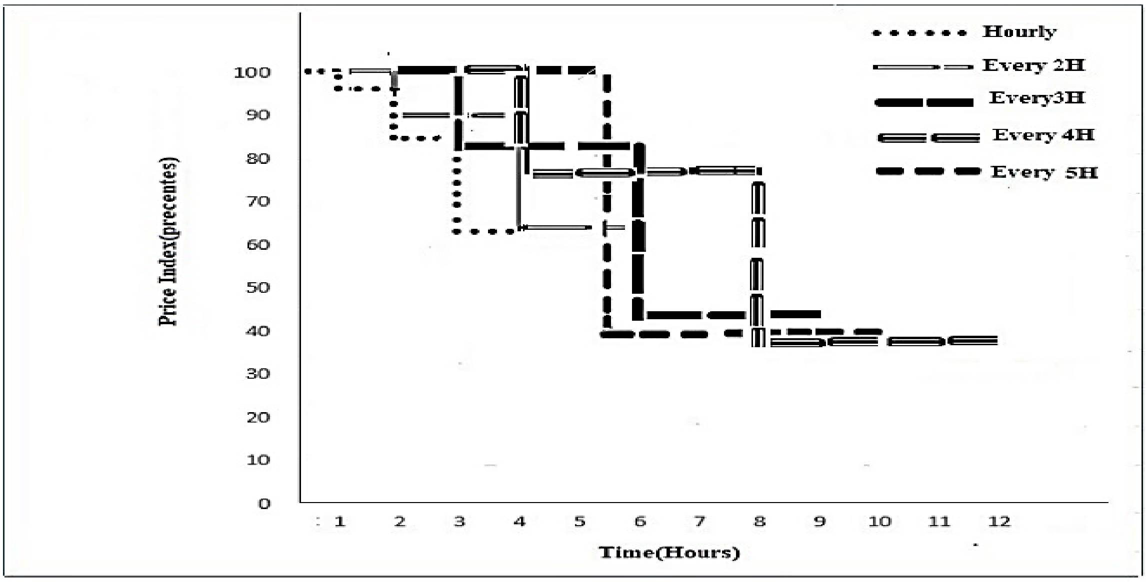

Chart 3- Price discounts over different periods (research findings)

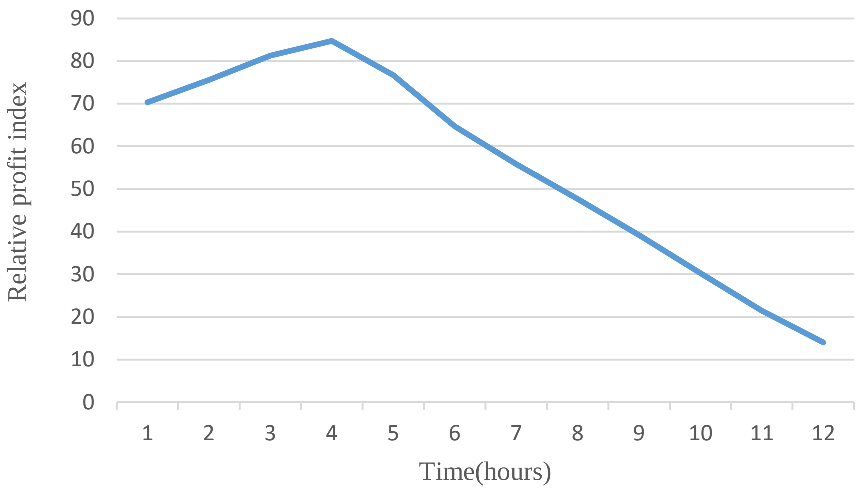

Chart 4- Profit trends in different discount periods
(Research findings)

The difference in profit depends on two factors: price reduction, which increases demand and sales; and quality reduction, which reduces demand and sales. As long as price reduction is more attractive to consumers than quality reduction is, the sales increase. But after the 4-hour interval, the negative impact of quality depreciation takes control over the attractiveness of price cutbacks, resulting in a decline in sales. Overall, 1- to 4-

hour discounts are better and achieve the maximum profit, while discounts over 10 hours lead to a great loss of profit. Thus, after a 4-hour gap, 3-hour and 5-hour discounts become better alternatives to increase sales and stay profitable, and long-term discounts need to be used cautiously and methodically.

Discussion

Optimal Discount Intervals

The findings of this study determine optimal discount times as a measure of profit maximization and wastage reduction of perishable goods such as tomatoes. The findings suggest that price discounts to be implemented within 3–4 hours to achieve the best outcomes.

This is a compromise between stimulating the demand from the consumers and maintaining the quality of the goods. Discounts with a smaller time gap between them (e.g., every 1–2 h) may lead to frequent price reduction, which can strip the profit and create an impression of low quality of the product. Discounts with larger intervals (e.g., every 5–7 h) can create more wastage, as the product quality is wasted heavily before sale. By applying discounts at 3 to 4-hour intervals, retailers can control their inventory turnovers while maintaining the perceived value of their offerings. Such a discovery is in line with prior studies involving dynamic pricing strategies that stress making adjustments in real time depending on the levels of quality deterioration, availability, and demand (Elmaghraby & Keskinocak, 2003).

For instance, Liu *et al.* (2023) demonstrated that data-driven dynamic pricing frameworks for omni-channel retailing can significantly reduce waste and increase profitability, especially in situations of unpredictable demands. Similarly, Elmaghraby & Keskinocak (2003) observed that early discounts would increase profit and reduce waste. Similarly, Kayikci *et al.* (2023) proposed a data-driven pricing framework that significantly reduced food waste and increased retail profitability. These studies altogether attest to the significance of evidence-based decision-making for maximizing pricing strategies for perishables, as illustrated in the current study, which reveals that short discount periods (1 to 4 hours) significantly maximize profitability while effectively controlling quality degradation and inventory levels.

Maintaining Quality Degradation

Quality degradation is a significant dilemma for retailers handling perishable products. The study found that tomatoes had a very severe quality loss within 24 hours, losing their quality index from 0.66 at the beginning of the day to 0.14 in the evening. This rapid spoilage is an indicator of the need for effective storage and stock management. For example, Sun *et al.* (2023) emphasized temperature and humidity management for the sake of maintaining product quality, which supports findings in the present study. Similarly, Kayikci *et al.* (2022) established that the inclusion of real-time environmental factors, such as temperature and humidity, into dynamic pricing equations can optimize sales while reducing wastage. To minimize degradation of quality, the retailers are urged to try and improve storage conditions, for example, keeping the products cool and dry.

Cold, dry storage of tomatoes can slow the process of degradation and extend their shelf life, as indicated by Sun *et al.* (2023). Additionally, retailers are urged to utilize "last chance" promotions to dispose of products nearing the end of their shelf life. These offers pressure buyers into buying the product before it spoils. It is as per the recommendation of Elmaghraby *et al.* (2003), who mention the application of dynamic discounts in reducing wastage and increasing profit. The study also highlights the applicability of including quality parameters in price models.

Through real-time tracking of quality decline, retailers can make evidence-based decisions regarding price adjustments and inventory management. This not only reduces wastage but also optimizes customer satisfaction as consumers receive the highest-quality products. Scholz & Kulko (2022) demonstrated that employing dynamic pricing models that depend on freshness would reduce food wastage by as much as 53.6% while optimizing retailer revenue by up to 10%. Liu *et al*. (2023) used reinforcement learning algorithms to improve the accuracy of prices by 35% and reduce waste, providing evidence for the advantage of real-time quality monitoring in the optimization of prices. All these findings together demonstrate the importance of data-driven decision-making in addressing perishable products. This research, despite providing valuable information on the dynamic pricing of perishable products, has some drawbacks. First, information was taken from only three stores within a single city, and consequently, the findings might be non-representative. Second, the model is based on homogeneous seller conduct and does not consider real external drivers such as weather, promotions, or rival prices. Third, actual-time quality was calculated based on estimated functions rather than direct technology or sensor readings. Future research can expand the geographic scope and utilize better quality monitoring tools or stronger market forces

Consumer Perception

This study highlights the critical role of consumer perception in dynamic pricing strategies. While discounts may increase demand, over-discounting may prompt consumers to doubt product quality and reduce brand trust and long-term loyalty. Zheng *et al.* (2022) illustrated that price-reduction discounts increase perceived quality uncertainty and therefore may have a detrimental effect on consumer purchase intentions. To be able to effectively balance price competition and brand image protection, stores have the option to use slow price cuts rather than drastic and deep price reductions. Drastic and sudden price cuts risk causing customers to question the freshness and quality of products, which can undermine brand trust and loyalty in the long term. Slow cuts allow customers to enjoy sustained value while still getting better prices in the long term. Aschemann-Witzel *et al.* (2015) point out that food purchasing is influenced by consumer attitudes and that deep discounting can send a hidden message of suboptimal quality, leading to more food waste as consumers avoid bargains.

Hence, an effective price strategy with price updates being aligned with product freshness can help in the reduction of waste and consumer trust protection. This practice not only promotes sustainable consumption behavior but also enhances the profitability overall through trust establishment and repeat purchases. The value of the goods must also be communicated to customers by retailers. For example, projecting the freshness and quality of tomatoes through the installation of signs within the stores or executing digital promotions can instill that the good is value for the price even after discounting. This is in concordance with the appeal of Syed *et al.* (2024) that transparency and communication are key in maintaining consumer satisfaction and trust. By having trusting and transparent relationships with consumers, retailers can enhance their brand reputation and provide long-term profitability, as shown in previous studies by data-driven and consumer-driven pricing approaches.

Conclusion

This study demonstrates the importance of dynamic pricing methods to manage perishable commodities such as tomatoes. Through the imposition of price discounts at optimal time intervals, retailers can maximize profit, avoid wastage, and maintain product quality. From these findings, it is suggested that discounts must be applied every 3–4 hours for optimal results. This approach strikes a balance between stimulating demand and protecting product value, enabling retailers to manage their inventories effectively while meeting consumers. Proper storage and inventory handling practices also need to be emphasized to minimize quality loss, according to this study. By maintaining temperature and humidity levels and employing "last chance" promotions, retailers can extend the shelf life of their products and reduce waste. Furthermore, this study sheds light on the importance of consumers' price strategy perception. Brand image and price attractiveness must be well balanced by retailers in a way that will capture customers' trust and loyalty. Future research should also examine whether these strategies are effective in other perishable products, such as dairy, meat, and bakery, and in alternative market environments. In addition, future studies can investigate the effects of emerging technologies such as artificial intelligence and blockchain on maximizing the dynamic pricing and inventories of perishable goods. The problems of dealing with perishable products can be addressed and sustainable business encouraged by improving and innovating even more for retailers. The results of the present research are as follows:

1. Discounting prices at optimal time periods (every 3–4 hours) maximizes profit with the least amount of waste.
2. It is a perfect trade-off between stimulating demand and product value.
3. Consumers' perception and expectations play vital roles in pricing strategies, and retailers must strike a balance between price appeal and product quality.

These findings show that dynamic pricing and smart inventory control can help retailers make efficient use of perishable products.

Suggestions for future research incorporating other factors affecting quality, i.e., temperature, humidity, and variety.

• Exploring the impact of consumers' price expectations on the demand function.

• Enlarging the study to other perishables such as dairy, meat.

• Exploring the use of new technology in optimizing dynamic pricing and inventory management, e.g., artificial.

Acknowledgments

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Appendix

Heteroskedasticity Test: Breusch-Pagan-Godfrey Null hypothesis: Homoskedasticity

Model Statistics	**Price Change** Stat. (p-Value)	**Demand**
F-statistic	2.13(0.097)	2.348(0.053)
Obs*R-squared	6.3248(0.097)	9.287(0.054)
Scaled explained SS	3.468(0.3249)	11.719(0.02)

Test to detect collinearity

D.V: Price Change	**Centered VIF**	**D.V: Demand**	**Centered VIF**
PRICE	1.200543	(PRICE_INDEX)^-1	1.756014
QUALITY	1.181043	QUALITY_INDEX^5	1.793120
REMAIN	1.040684	PERIOD^2	1.080800

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ارائه الگویی برای استرتژی تخفیف قیمت در محصولات فاسدشدنی: مطالعه موردی گوجه‌فرنگی تازه

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چکیده

بسیاری از محصولات کشاورزی تازه، مانند میوه‌ها و سبزیجات، به‌شدت فسادپذیر هستند و حفظ کیفیت آن‌ها از طریق نگهداری در شرایط سردخانه‌ای یا شرایط بهینه، می‌تواند برای خرده‌فروشان و تولیدکنندگان کوچک از نظر اقتصادی چالش‌برانگیز باشد. گاهی این محصولات در کمتر از ۲۴ ساعت کیفیت و بازار پسندی خود را از دست می دهند. لازم است خرده‌فروش با استفاده از استراتژی تخفیف قیمت متناسب با کاهش کیفیت از هدر رفتن سرمایه خود جلوگیری کند. چالش اصلی در اتخاذ این استراتژی، تعیین زمان و میزان تخفیف قیمت است. برای بهینه‌سازی تنزیل قیمت، چهار تابع باید برآورد شود: الف) تابع کیفیت وابسته به زمان، ب) تابع تغییر قیمت، ج) تابع تقاضا که تابعی از قیمت و کیفیت است، و د) تابع هدف که در اینجا به‌عنوان تابع سود خرده‌فروش در نظر گرفته می‌شود. ما از مدل‌های قیمت‌گذاری پویا استفاده می‌کنیم که عواملی مانند کاهش کیفیت، سطح موجودی، و رفتار مصرف‌کننده را ادغام می‌کند. برای ارائه بینش واقعی، داده‌های تحقیق از سه فروشگاه میوه و تره‌بار در شهر گرگان جمع‌آوری شد. مدت زمان سه ماه و شامل تمام روزهای کاری بود. از هر فروشنده خواسته شد تا قیمت و مقدار فروش را به‌صورت ساعتی از ابتدا تا پایان روز کاری گزارش دهد. به این ترتیب از هر فروشگاه حدود ۱۰۰۰ داده ثبت شد. گوجه‌فرنگی به‌دلیل مصرف گسترده، عرضه مداوم و فسادپذیری سریع به‌عنوان مطالعه موردی انتخاب شد. نتایج نشان می‌دهد که تخفیف‌های قیمت می‌تواند به‌طور قابل‌توجهی سودآوری را افزایش دهد و در عین حال خطر محصولات فروخته نشده و فاسد را کاهش دهد. به‌طور خاص، یافته‌ها نشان می‌دهد که اجرای تخفیف‌های قیمتی هر ۳ تا ۴ ساعت، بیشترین سودآوری را به همراه داشته است. میانگین تخفیف ۳۵ درصد است که منجر به افزایش ۸۲ درصدی سود ناخالص می‌شود. در مقابل، فواصل تخفیف کوتاه‌تر (هر ۱ تا ۲ ساعت) با میانگین تخفیف ۱۸ درصد، سود ناخالص را تا ۷۳ درصد بهبود بخشید. از سوی دیگر، فواصل تخفیف‌های طولانی‌تر (هر پنج تا هفت ساعت) با میانگین تخفیف ۴۶ درصد منجر به افزایش ۶۶ درصدی سود ناخالص شد. علاوه بر این، این مطالعه بر اهمیت درک مصرف‌کننده در موفقیت استراتژی‌های قیمت‌گذاری پویا تأکید می‌کند. تخفیف بیش از حد می‌تواند منجر به درک کیفیت پایین محصول شود که ممکن است بر اعتماد مصرف‌کننده و اعتبار طولانی مدت فروشگاه تأثیر منفی بگذارد. پژوهش‌های آینده می‌توانند با افزودن متغیرهای مؤثر بر کیفیت محصول- مانند دما، رطوبت و نوع محصول- چارچوب فعلی را توسعه دهند. همچنین، تحلیل نقش انتظارات قیمتی مصرف‌کنندگان در شکل‌گیری تابع تقاضا، تعمیم مدل به سایر محصولات فسادپذیر از جمله لبنیات و گوشت، و استفاده از فناوری‌های نوین نظیر هوش مصنوعی و بلاک‌چین در بهینه‌سازی قیمت‌گذاری پویا و مدیریت موجودی، می‌تواند در ارتقای اثربخشی راهبردهای فروش محصولات فسادپذیر نقش مهمی ایفا کند.

واژه‌های کلیدی: استراتژی قیمت‌گذاری پویا، بازارهای خرده‌فروشی، تخفیف‌های قیمتی، کاهش کیفیت، گوجه‌فرنگی

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Identifying and Classifying Factors Influencing Consumers' Purchase Intention toward Antibiotic-Free Poultry: Evidence from Mashhad, Iran

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Abstract

Poultry production is one of the fastest-growing industries worldwide, and poultry meat has become a primary protein source for many populations. To maximize growth in the shortest possible time, producers often rely on disease-preventing antibiotics and growth promoters. However, numerous studies have detected antibiotic residues in poultry meat, raising concerns about their contribution to antibacterial resistance in human pathogens. Consequently, consumer demand for healthier products—particularly antibiotic-free poultry—is steadily increasing. Although this trend is advancing globally, it is still in its early stages in Iran. Accordingly, in order to move towards the development of the market for healthy products, the first essential step is to identify the factors that influence household consumption patterns. This study employs a combination of three decision-making tools, including Interpretive Structural Modeling (ISM), MICMAC analysis, and Fuzzy BestWorst Method (BWM), to evaluate factors influencing the purchase of antibiotic-free poultry in Mashhad, Iran, a key market where such products are available and consumer trends are emerging, in 2025. The process begins with the ISM method, which constructs a hierarchical model to illustrate the influence and interdependence of these factors. This step is crucial for understanding their collective impact on consumer purchase intention. Subsequently, the MICMAC analysis categorizes these factors based on their levels of influence and dependence, identifying the most critical elements that create a competitive advantage. Finally, the fuzzy Best–Worst Method (BWM) is applied to assign weights to these key factors. The results indicate that consumer awareness is the highest weight, followed by attitude and subjective norms. Identifying these key factors and their interrelationships provides actionable insights for decision-makers and stakeholders for strategic planning and prioritization. Based on these findings, it is recommended that policymakers and marketers focus on increasing consumer awareness, shaping positive attitudes, and leveraging subjective norms to encourage the purchase of antibiotic-free poultry. Targeted educational campaigns, informative labeling, and marketing strategies tailored to consumer preferences can help enhance adoption and support healthier consumption patterns.

Keywords: Antibiotic-free, Marketing mix, Poultry

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Introduction

Broiler chickens are a significant source of meat worldwide (Muaz *et al.*, 2018). World meat production is projected to rise 13% to an estimated 406 million tons by 2034, with over half (55%) of the growth occurring in Asia. Poultry will lead this expansion, contributing 15 million tons to the increase and accounting for 62% of the additional meat produced in the next decade (OECD-FAO, 2025). This increased demand has led to more intensive poultry production systems, particularly for broiler chickens, to maximize output in the shortest period. Unlike traditional chicken production in open sheds, which takes 9 to 10 weeks, modern technologies enable production within 6 to 7 weeks (Apata, 2009). This advancement is often achieved through the use of antimicrobial growth promoters (AGPs) in feed (Yadav & Jha, 2019). However, because the elimination of antibiotics from an animal's body is a time-consuming process, the use of antibiotics in veterinary medicine can result in drug residues in animal products such as meat (Nikoukar & Bazzi, 2016). Antibiotic residues in meat can cause allergic reactions and weaken the immune system (Dewdney *et al.*, 1991; Centner, 2016). Therefore, reducing the effectiveness of antibiotics and the rise of microbial resistance due to widespread antibiotic use is a major human health challenge (Abreu *et al.*, 2023; Al Sattar *et al.*, 2023). Minimizing antibiotic use in food-producing animals, such as poultry, cattle, and pigs, is essential in this effort (Dewdney *et al.*, 1991; Centner, 2016).

The global health implications of antibiotic resistance were highlighted by the World Health Organization (WHO) in 1997, declaring it a public health crisis (Tajodini et al., 2015). The Centers for Disease Control and Prevention (CDC) and the FAO have also raised alarms about antimicrobial resistance, which poses a significant threat to global health (CDC, 2013; FAO, 2015). To promote the production of healthy products and improve food safety, the European Union banned the use of antibiotics in chicken meat production in 2006 (Dewdney, 1991; Centner, 2016). Consequently, concerns about antimicrobial resistance and growing consumer preference for antibiotic-free (ABF) poultry have prompted several countries to restrict or ban the use of AGPs (Stokka, 2016; FDA, 2021). Sweden was the first country to ban AGPs in 1986 (Dibner & Richards, 2005; Wenk, 2000), and the European Union followed suit in 2006 (Kulshreshtha *et al.*, 2014; Hafeez *et al.*, 2016).

Consumer demand for products raised without routine antibiotic use is driving a growing movement toward antibiotic-free meat production (Dimitri, 2005). According to the U.S. Department of Agriculture's Food Safety and Inspection Service (USDA-FSIS), "antibiotic-free poultry" refers to meat from birds that have not consumed antibiotics in food or water and have not been injected with antibiotics (Cervantes, 2015). The shift toward ABF poultry is part of a broader consumer preference for safer, antibiotic-free food, driven by concerns about health, environmental impact, animal welfare, and food quality.

In developed countries, the demand for healthy food products, such as antibiotic-free poultry, has increased due to improved living standards, the growing importance of health, and increasing consumer awareness of the benefits of healthy products (Ditlevsen *et al.*, 2019; Willett *et al.*, 2019). Since 1990, sales of antibiotic-free and organic foods have grown by 20% annually, according to the United States Organic Trade Association (Cervantes, 2015). Global demand for and willingness to pay for healthy food products are rapidly increasing (Li & Kallas, 2021).

In Iran, poultry meat production is undergoing progressive development and expansion. Over the past four decades, investment in this sector has grown significantly, making poultry production one of Iran's most important economic activities (Kamalzadeh *et al.*, 2009). The results of the 2024 poultry slaughtering census in Iran indicate that a total of 1,392 million live poultry were brought to slaughterhouses, with a total weight of 3,527 thousand tons. Of these, 1,378 million usable carcasses weighing 2,682 thousand tons were produced. Chicken, with 2,605 thousand tons, accounted for 97.1 percent of the total usable poultry weight. Among provinces, Khorasan Razavi produced over 198 thousand tons, ranking fourth in the country in total poultry production (Statistical Center of Iran, 2025). Despite the increasing demand for healthy food products, including antibiotic-free chicken, in other countries, its consumption has not yet become widespread among Iranian consumers (Nikoukar & Bazzi, 2016). However, studies conducted in Mashhad, the capital of Khorasan Razavi, have shown that consumer awareness and demand for healthy products - organic and antibiotic-free - are growing (Mohammadi *et al.*, 2023; Ghorbani *et al.*, 2019; Aghasafari & Karbasi, 2021). These findings highlight the importance of understanding consumer preferences and behaviors in this region to inform production and investment decisions and to support the development of the antibiotic-free chicken market in Iran.

Research on organic food, healthy food, and consumption behavior is prevalent in Europe and other Western countries. This includes profiling buyers (Hansen *et al*., 2018; Petrescu *et al*., 2017), motivations for buying (Petrescu *et al*., 2017; Pham *et al*., 2018; Scalvedi & Saba, 2018; Sobhanifard, 2018), purchase intentions (Asif *et al*., 2018; Çabuk *et al*., 2014; Ham *et al*., 2018; Hsu & Chen, 2014; Lee & Yun, 2015; Mainardes *et al*., 2017; Pham *et al*., 2018; Prakash *et al*., 2018), willingness to pay (Tong Hu *et al*., 2024; Lim *et al*., 2014), and consumer attitudes (Çabuk *et al*., 2014; Chekima *et al*., 2017; Janssen, 2018; Mainardes *et al*., 2017; Singh & Verma, 2017). Nevertheless, it is essential to explore existing literature on consumers' behavior regarding organic and healthy foods, particularly poultry products. Mohammadi *et al*. (2023) found that awareness of the nutritional benefits of ABF poultry meat, the head of household's education, monthly family income, and advertising had positive impacts, while price had a negative impact on consumption.

Researchers have also extensively investigated consumers' willingness to pay (WTP) for poultry products, focusing on various attributes that influence purchasing decisions. For instance, Chen *et al*. (2024) examined consumers' WTP for carbon-labeled beef, highlighting the growing interest in environmentally sustainable meat products and how eco-labels can affect price sensitivity and purchase intention. Thuannadee & Noosuwan (2023) studied locally produced organic chicken, demonstrating that consumers are willing to pay a premium for products perceived as healthier and locally sourced, reflecting a combination of health consciousness and support for local producers. Similarly, Saha *et al*. (2022) and Jahanabadi *et al*. (2024) explored WTP for safe chicken meat, emphasizing the importance of food safety and traceability in shaping consumer decisions. Earlier studies on organic chicken by Gifford & Bernard (2011) and Gunduz *et al*. (2011) showed that consumers' WTP is strongly influenced by perceptions of product quality, nutritional benefits, and ethical considerations related to animal welfare. Van Loo *et al*. (2011) analyzed the effect of organic labels on chicken breast, indicating that labeling can significantly enhance perceived value and justify higher prices.

In general, the literature review indicates that various factors influence healthy food purchase intentions. However, antibiotic-free chicken meat is a relatively new concept, especially in developing countries like Iran, where food security remains a major concern. Consequently, there is limited research comprehensively examining the determinants of purchase intention for antibiotic-free chicken in Iran. This study aims to address this gap by identifying and prioritizing the critical factors affecting purchase intention, determining their hierarchical relationships, and developing a comprehensive model. To achieve this, a fuzzy hybrid Multi-Criteria Decision-Making (MCDM) model is proposed, integrating Interpretive Structural

Modeling (ISM), MICMAC analysis, and the fuzzy Best-Worst Method (BWM) to account for uncertainty and subjective judgments.

Materials and Methods

This study employed the ISM-MICMAC-FBWM methodology for analysis. Initially, influential indicators were identified from the existing literature and subsequently validated and contextualized through expert consultation. In the ISM phase, an initial reachability matrix was constructed based on these indicators. Following its refinement, the final ISM model was developed, accompanied by MICMAC analysis. Finally, in the Fuzzy BWM phase, pairwise comparisons of the key criteria derived from the ISM model were generated, and their respective weights and rankings were determined. The step-by-step research process is illustrated in Fig. 1. As this research is exploratory, it does not formulate hypotheses but instead addresses three research questions:

1. What factors influence the research objective?
2. How do these influential factors interact, and what are their causal relationships?
3. What are the weights and rankings of these factors in relation to the research objective?

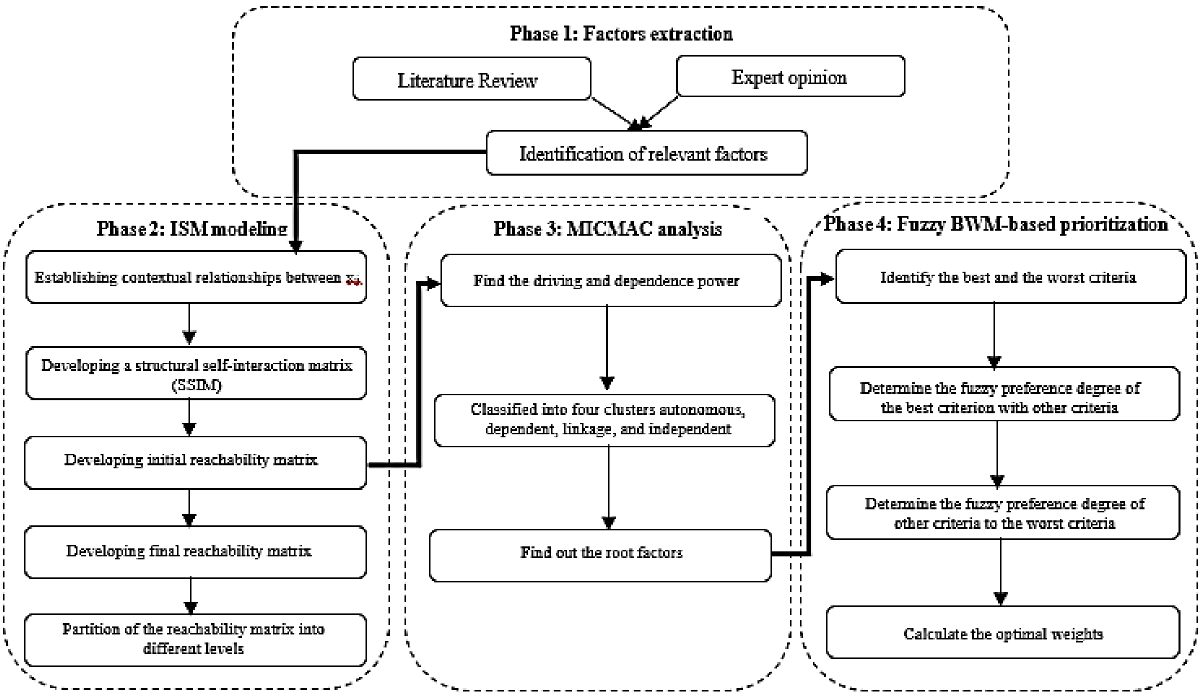

Figure 1- Framework of the approach

Interpretive Structural Modeling (ISM) Warfield first presented the Interpretive Structural Modeling (ISM) in 1974. ISM is a decision-making technique that shows the interaction between different variables and displays the relationships between variables in the form of hierarchical relationships (Warfield, 1974). It helps describe intricate issues and develop structured relationship models (Sheykhan *et al.*, 2024). ISM focuses on experts' experience and knowledge in defining the contextual relationships of a complicated system (Bouzon *et al.*, 2015). This approach addresses the shortcomings and challenges encountered in traditional methods like weighted score and structural equation modeling and provides a better understanding of system behavior (Wan *et al.*, 2022). Different stages of ISM are explained in the following.

Step 1. Identify the influential factors: Identify and determine influential factors through a literature review, group discussion, and brainstorming.

Step 2. Forming a Structural self-interaction matrix (SSIM): At this step, the variables are arranged in rows and columns, and either of the following relationships is defined for different variable pairs (Agarwal *et al.*, 2023):

- V: factor X_i will influence the factor X_j.
- A: factor X_j will influence the factor X_i.
- X: factor Xi and factor Xj will influence each other.
- O: factor Xi and factor Xj are unrelated.

Step 3. Forming initial reachability matrix (IRM): The SSIM needs to be converted into a binary matrix called the initial reachability matrix (Bouzon *et al.*, 2015). The reachability matrix is the path that indicates whether one capability factor can establish a path of arrival with another factor through the indirect action of other factors (Ahmadi, 2023; Singh *et al.*, 2024). By converting different symbols of the SSIM into 0 and 1, one can obtain the IRM (Agarwal *et al.*, 2023). The following rules shall be followed to prepare the IRM:

- If X_{ij} is represented by V in the SSIM, then X_{ij} and X_{ji} are converted to 1 and 0 in the IRM, respectively.
- If X_{ij} is represented by A in the SSIM, then X_{ij} and X_{ji} are converted to 0 and 1 in the IRM, respectively.
- If X_{ij} is represented by X in the SSIM, then both X_{ij} and X_{ji} are converted to 1 in the IRM.
- If X_{ij} is represented by O in the SSIM, then both X_{ij} and X_{ji} are converted to 0 in the IRM.

Step 4. Forming final reachability matrix (FRM): Considering the additive association of different elements, one needs to make the IRM consistent. For example, if Factor A leads to Factor B and then Factor B leads to Factor C, then Factor A shall lead to Factor C as well, and if the reachability matrix cannot reflect this relationship, it must be corrected to replace the missed relationships. To this end, one must elevate the IRM to the power of K + 1 (K ≥1), in such a way that a stable state is established ($M^K = M^{K+1}$). Albeit, the powering of the matrix shall be done via Boolean matrix multiplication. According to this multiplication scheme, 1 × 1 = 1 and 1 + 1 = 1. In this way, some of the zero elements turn into 1s, which are then denoted as 1* (Agarwal *et al.*, 2023).

Step 5. Determining the level of variables: Each of the system components has two different sets of antecedent (A) and reachability (R) that play a fundamental role in the structure of the final model as well as the design of the system. To determine the level and priority of factors, using the final accessibility matrix, these two sets are obtained for each factor (Wang *et al.*, 2020). The reachability set consists of horizontal factors, while the antecedent set consists of vertical factors (Sindhwani & Malhotra, 2017). The intersection between these two sets is then derived for all factors. The factors for which the reachability and the intersection sets are the same are placed at the top level of the ISM hierarchy (Sindhwani & Malhotra, 2017; Mangla *et al.*, 2014; Bouzon *et al.*, 2015). When the factors of the highest level are identified in the first iteration, these factors should be removed from other factors. The same process is repeated until the level of each factor is determined (Rajesh, 2017; Sindhwani & Malhotra, 2017; Lim *et al.*, 2017). Based on the determined levels and relationships between the factors, they can be drawn as a structural model.

MICMAC analysis: The main purpose of the MICMAC technique is to analyze the driving power and independence power of the variables (Gupta *et al.*, 2016). This technique relies on the principle of matrix multiplication to ascertain how variables interact with each other by analyzing the interactive relationship among different subsystems within a complex system (Chen & Qiang, 2023). The factors are classified into four clusters based on the driving and dependence powers derived from the Final Reachability Matrix (FRM). To draw the diagram, the driving power of the factors is represented as a vertical axis, and the dependence power is represented as the horizontal axis. The factors are categorized as autonomous, dependent, linkage, and independent based on their driving and dependence powers (Hasan *et al*., 2024).

Autonomous factor: these factors exhibit Low driving and dependence power. In other words, such factors have weak connections with the overall system. They play a crucial role in mediating relationships between factors, affecting those in the preceding layer while being constrained by factors in the subsequent layer (Rathi *et al*., 2023).

Dependent factor: They exhibit weak driving power and high dependency power. They show little influence on the system but are highly influenced by the system (Maleki Toulabi *et al*., 2024).

Linkage factor: These factors exhibit strong driving and dependence power, and in fact, these factors are unstable. This property is because any change in them can affect other factors and produce a feedback loop, influencing themselves in return (Zhang *et al*., 2024).

Independent factor: these factors exhibit Low dependence power but high driving power. Independent factors are known as key factors because they are the foundation of the model, and for success, special attention should be paid to these factors (Rathi *et al*., 2023).

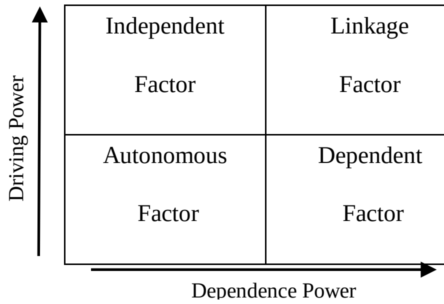

Figure 2- MICMAC diagram (Driving Power-Dependence Power)

Fuzzy Best-Worst Method: To prioritize the identified criteria for purchasing antibiotic-free poultry meat, the fuzzy best–worst method is adopted in this paper. In an MCDM problem, several alternatives are evaluated with respect to a number of criteria to select the best alternative(s) (Banihashemi, 2023). The best–worst method (BWM) is one of the MCDM methods presented by Rezaei (2015), which can obtain decision results using fewer pairwise comparisons compared to AHP (Huang *et al*., 2023). BWM is based on pairwise comparisons between criteria (Banihashemi, 2023). First, the best criterion (e.g., most desirable, most important) and the worst criterion (e.g., least desirable, least important) are identified, then the priority of the best criterion, compared to the number of criteria, as well as the degree of superiority of all criteria to the worst criterion, are determined using pairwise comparisons (Rezaei *et al*., 2016; Gupta & Barua, 2016; Amiri *et al*., 2021). The best criterion is the one that has the most vital role in making the decision, while the worst criterion has the opposite role in the decision process. Furthermore, the BMW does not only derive the weights independently but it can also be combined with other multi-criteria-decision-making methods (Amoozad Mahdiraji *et al*., 2018; Kolagar, 2019; Kumar, 2019).

Verbal and linguistic judgments made by decision-makers are usually vague and uncertain. Therefore, the fuzzy best–worst method (FBWM) was developed by Guo & Zhao (2017) to determine the importance weights of the identified components and sub-components. The steps of the FBWM in obtaining the priorities are as follows:

Step 1: Identify the best and the worst criteria: in this step, the best and the worst criteria are determined using experts' opinions.

Step 2: Pairwise comparison of the best criterion with other criteria: in this step, pairwise comparisons can be made using any fuzzy spectrum, but one of the most common spectrums for the fuzzy BWM method is based on the five-point Likert scale outlined in Table 1.

Table 1- Transformation rules of linguistic terms.

Linguistic term	Triangular fuzzy number
Equally Important (EI)	(1,1,1)
Weakly Important (WI)	(2/3,1,3/2)
Fairly Important (FI)	(3/2,2,5/2)
Very Important (VI)	(5/2,3/7/2)
Absolutely Important (AI)	(7/2,4,9/2)

The best vector compared to other criteria is as follows:

$$\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots, \tilde{a}_{Bn}) \quad (1)$$

Where $\tilde{A}_B$ expresses the fuzzy best vector compared to other criteria and $\tilde{a}_{Bj}$ expresses the fuzzy preference of the best criterion C_B compared to criterion j. It is clear that $\tilde{a}_{BB}$= (1,1,1).

Step 3: Pairwise comparison of the other criteria with the worst criterion: Similarly, the fuzzy preferences of all criteria, with respect to the worst criterion, were determined using the linguistic variables presented in Table 1, as follows:

$$\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW}) \quad (2)$$

Where $\tilde{A}_W$ expresses the fuzzy worst vector compared to other criteria, and $\tilde{a}_{jW}$ expresses the fuzzy preference of criterion i compared to the worst criterion C_W. It is clear that $\tilde{a}_{WW}$= (1,1,1).

Step 4: Calculate the optimal weights $(\tilde{W}_1^{\ *}, \tilde{W}_2^{\ *}, \dots, \tilde{W}_n^{\ *})$: The weights of the criteria and $\tilde{\xi}^*$ can be calculated using the following non-linear mathematical programming model. It is recommended to transform this model into a linear mathematical programming model for several criteria more than three to obtain better results (Guo & Zhao, 2017).

$$\begin{aligned} &\min \xi \\ &s.t. \\ &\left|\frac{\tilde{W}_b}{\tilde{W}_j} - \tilde{a}_{Bj}\right| \le \tilde{a} \quad for\ all\ j \\ &\left|\frac{\tilde{W}_j}{\tilde{W}_w} - \tilde{a}_{jW}\right| \le \tilde{a} \quad for\ all\ j \\ &\sum_j R(\tilde{W}_j) = 1 \\ &l_j^w \le m_j^w \le u_j^w \ , \quad l_j^w \ge 0 \quad W_j \ge 0 \quad for\ all\ j \end{aligned} \quad (3)$$

These values are used in the relation $R(\tilde{a}_i) = \frac{l_i + 4m_i + u_i}{6}$.

Step 5: Determine the consistency ratio: Consistency ratio (CR) is an important indicator to check the consistency degree of pairwise comparison; hence, it is necessary to calculate the consistency ratio of the pairwise comparison. In fuzzy BWM, the consistency ratio is calculated as:

$$CR = \frac{\tilde{\xi}^*}{\zeta} \quad (4)$$

Where $\tilde{\xi}^*$ is obtained by solving Eq. (3), and max ζ is the consistency index, which is shown in Table 2.

Table 2- Transformation rules of linguistic terms.

Linguistic term	a_{BW}	CI (max ζ)
Equally Important (EI)	(1,1,1)	3/00
Weakly Important (WI)	(2/3,1,3/2)	3/80
Fairly Important (FI)	(3/2,2,5/2)	5/29
Very Important (VI)	(5/2,3/7/2)	6/69
Absolutely Important (AI)	(7/2,4,9/2)	8/04

Data Collection

To identify the factors influencing consumers' purchase intention toward antibiotic-free poultry meat, data were collected in 2025 from ten purposively selected experts in Mashhad, Iran. These experts represented academia, the poultry and food industries, and organic food suppliers, and were selected based on their experience and knowledge of consumer behavior and the antibiotic-free poultry market. Semi-structured interviews were initially conducted to generate a comprehensive list of potential factors. Overlapping or irrelevant items were then removed, resulting in a refined set of 16 criteria. For the ISM stage, individual expert responses were aggregated using the frequency method to form a consensus Structural Self-Interaction Matrix (SSIM), which served as the input for the ISM–MICMAC analysis. The same experts then evaluated these criteria through a structured questionnaire designed for pairwise comparisons. At this stage, expert judgments were combined using the aggregated fuzzy preference weighted mean method, enabling a reliable estimation of the final priority scores. The entire data collection and aggregation process took approximately 25 days. The final set of 16 criteria used in the analysis is presented in Table 3.

Table 3- Factors affecting the purchase intention antibiotic-free poultry meat

Denotations	Criteria	Description	Reference
S_1	Loyalty	Consumers' tendency to repeatedly purchase a specific brand or product is influenced by trust and satisfaction .	Oliver, 1999
S_2	Consumer awareness	The level of knowledge and information consumers have about the benefits and features of antibiotic-free and healthy products.	Mohammadi *et al.*, 2023
S_3	Eating habits	Consumer dietary patterns and preferences that affect the selection of healthy products.	Mizia *et al.*, 2021
S_4	Uncertainty	Consumers' perceived uncertainty about product quality, safety, or availability, influencing their purchase decisions.	Nikoukar & Bazzi, 2016
S_5	Cognitive factors	Mental processes such as attention, memory, and information processing that affect consumer behavior toward healthy products.	Pham *et al.*, 2018
S_6	Attitude	Overall positive or negative evaluation of healthy and antibiotic-free products that influences purchase intention	Ajzen, 1991
S_7	Perceived behavior control	Consumers' perceived ability or control over purchasing and accessing healthy products.	Ajzen, 1991
S_8	Marketing mix	The effect of product, price, place, and promotion strategies on consumer purchasing behavior	Kotler & Keller, 2016
S_9	Preference for conventional products	Consumer tendency to choose conventional products over healthier alternatives, often due to familiarity or lower	Chen *et al.*, 2024
S_{10}	Myopia	Short-term focus of consumers, prioritizing immediate benefits such as low price over long-term health advantages.	Sheth *et al.*, 1991
S_{11}	Fatalism	Belief that outcomes are predetermined or beyond one's control, affecting the likelihood of choosing healthy products	Ssewanyana *et al.*, 2015
S_{12}	Demographic factors	Characteristics such as age, gender, income, and education that influence consumer preferences and buying behavior.	Wojciechowska-Solis & Sorok, 2017
S_{13}	Subjective norms	Social pressure and expectations that affect consumers' decisions to purchase healthy products	Ajzen, 1991
S_{14}	Perceived value	Consumers' evaluation of product value, considering quality relative to price, influencing purchase decisions	Zeithaml, 1988
S_{15}	Purchasing effectiveness	Consumers' ability to select and buy products efficiently according to their needs and available resources	Kotler & Keller, 2016
S_{16}	Indifference	Lack of preference or attention between healthy and conventional products, often due to limited information or awareness	Lim *et al.*, 2014

Results and Discussion

ISM Results

The Structural Self-Interaction Matrix (SSIM) shows the pairwise comparisons of these factors as evaluated by experts (Table 4). The SSIM highlights which factors are considered to have direct influence on others, providing initial insights into the interrelationships among variables. For example, factors such as marketing mix (S8) and demographic factors (S12) appear frequently as influencers in the matrix, suggesting they may serve as driving variables in the system. Conversely, factors like S1 (Loyalty) and S5 (Cognitive Factors) appear more dependent on other variables. This preliminary analysis guides the subsequent steps in the ISM process to develop the final hierarchical structure and prioritize the factors for strategic focus.

The initial reachability matrix (IRM) is obtained by converting the SSIM to a binary matrix, where the elements on the primary diagonal are set to 1. Table 5 displays the IRM obtained after conversion.

Table 4- Structural self-interaction matrix

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}
S_1	-	A	O	O	O	A	O	O	O	A	A	O	O	O	A	O
S_2		-	V	V	A	V	V	A	V	V	V	A	X	V	V	A
S_3			-	A	A	V	O	O	V	A	A	O	A	O	V	O
S_4				-	A	V	O	O	V	V	V	O	A	V	V	V
S_5					-	O	O	A	V	V	V	A	O	O	O	V
S_6						-	V	A	V	V	V	O	A	V	V	A
S_7							-	O	A	O	O	O	A	O	A	A
S_8								-	O	O	O	O	V	O	O	O
S_9									-	V	V	O	A	O	V	A
S_{10}										-	V	O	A	O	O	X
S_{11}											-	O	A	V	O	A
S_{12}												-	O	O	O	O
S_{13}													-	V	O	A
S_{14}														-	A	A
S_{15}															-	O
S_{16}																-

Table 5- Initial Reachability Matrix.

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}
S_1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S_2	1	1	1	1	0	1	1	0	1	1	1	0	1	1	1	0
S_3	0	0	1	0	0	1	0	0	1	0	0	0	0	0	1	0
S_4	0	0	1	1	0	1	0	0	1	1	1	0	0	1	1	1
S_5	0	1	1	1	1	0	0	0	1	1	1	0	0	0	0	1
S_6	1	0	0	0	0	1	1	0	1	1	1	0	0	1	1	0
S_7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
S_8	0	1	0	0	1	1	0	1	0	0	0	0	1	0	0	0
S_9	0	0	0	0	0	0	1	0	1	1	1	0	0	0	1	0
S_{10}	1	0	1	0	0	0	0	0	0	1	1	0	0	0	0	1
S_{11}	1	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0
S_{12}	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0
S_{13}	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	0
S_{14}	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
S_{15}	1	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0
S_{16}	0	1	0	0	0	1	1	0	1	1	1	0	1	1	0	1

Once the binary IRM was developed, the relationships among variables were examined to identify both direct and indirect associations. The final reachability matrix (FRM) was then constructed to account for secondary associations, reflecting the transitive impacts that were not captured in the initial IRM. For example, the IRM suggested no direct relationship between $S3$ and $S1$. However, the FRM analysis revealed that $S3$ influences $S1$ indirectly through $S6$. This indicates that $S3$ has an indirect but significant role in the system, highlighting its potential impact on $S1$ via mediating factors. Such adjustments in the FRM ensure that all transitive relationships are appropriately captured, providing a more complete understanding of the interconnections among variables. Overall, the FRM results demonstrate that some factors previously considered independent actually exert influence through intermediary variables, emphasizing the importance of considering indirect effects when analyzing complex systems. This insight guides prioritization of factors for further analysis and intervention. Finally, IRM was transformed into FRM using strict logic. Table 6 describes the FRM formed by checking transitivity.

Table 6- Final reachability matrix

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	Driving power
S_1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
S_2	1	1	1	1	0	1	1	0	1	1	1	0	1	1	1	1*	13
S_3	1*	1*	1	1*	0	1	1*	0	1	1*	1*	0	1*	1*	1	1*	13
S_4	1*	1*	1	1	0	1	1*	0	1	1	1	0	1*	1	1	1	13
S_5	1*	1	1	1	1	1*	1*	0	1	1	1	0	1*	1*	1*	1	14
S_6	1	1*	1*	1*	0	1	1	0	1	1	1	0	1*	1	1	1*	13
S_7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
S_8	1*	1	1*	1*	1	1	1*	1	1*	1*	1*	0	1	1*	1*	1*	15
S_9	1*	1*	1*	1*	0	1*	1	0	1	1	1	0	1*	1*	1	1*	13
S_{10}	1	1*	1	1*	0	1*	1*	0	1*	1	1	0	1*	1*	1*	1	13
S_{11}	1	1*	1	1*	0	1*	1*	0	1*	1*	1	0	1*	1	1*	1*	13
S_{12}	1*	1	1*	1*	1	1*	1*	0	1*	1*	1*	1	1*	1*	1*	1*	15
S_{13}	1*	1	1	1	0	1	1	0	1	1	1	0	1	1	1*	1*	13
S_{14}	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
S_{15}	1	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	4
S_{16}	1*	1	1*	1*	0	1	1	0	1	1	1	0	1	1	1*	1	13
Dependence power	14	12	12	12	3	12	14	1	12	12	12	1	12	14	13	12	

The next step is partitioning FRM into distinct levels. During this step, the hierarchical structure of factors influencing the purchase intention of Antibiotic-Free poultry meat by using ISM. Based on the condition of $(Si) = (Si) \cap (Si) = R(Si)$, the influencing factors were classified at different levels. The hierarchical structure is as follows: Level 1=S_1, S_7, S_{14}, Level 2=S_{15}, Level 3=$S2$, S3, S_4, S_6, S_9, S_{10}, S_{11}, S_{13}, S_{16}, Level 4=S_5, Level 5=S_8, S_{12}. In the social media context, the reachability set (Si), antecedent set (Si), intersection (Si), and level partitions are listed in Table 7.

Table 7- Level partition-interaction

	Reachability set	Antecedent set	Intersection set	Level
S_1	1	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 15, 16,	1	1
S_2	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3
S_3	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3
S_4	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3
S_5	5	5, 8, 12,	5	4
S_6	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3
S_7	7	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 15, 16,	7	1
S_8	8	8	8	5
S_9	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3
S_{10}	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3
S_{11}	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3
S_{12}	12	12	12	5
S_{13}	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3
S_{14}	14	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16,	14	1
S_{15}	15	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 15, 16,	15	2
S_{16}	2, 3, 4, 6, 9, 10, 11, 13, 16,	2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 16,	2, 3, 4, 6, 9, 10, 11, 13, 16,	3

In the next step, an interpretive structural model was developed using the calculated scores for each index and the completed outcome matrix. The resulting model, shown in Fig. 3, comprises five levels. At the fifth level, two criteria, namely "Marketing mix" and "Demographic factors" are identified as the most influential criteria that directly impact the Cognitive criterion at the fourth level. This influence is hierarchical, with the three criteria at the first level, namely "Loyalty," "Perceived behavior control," and "Perceived value," being the most influential.

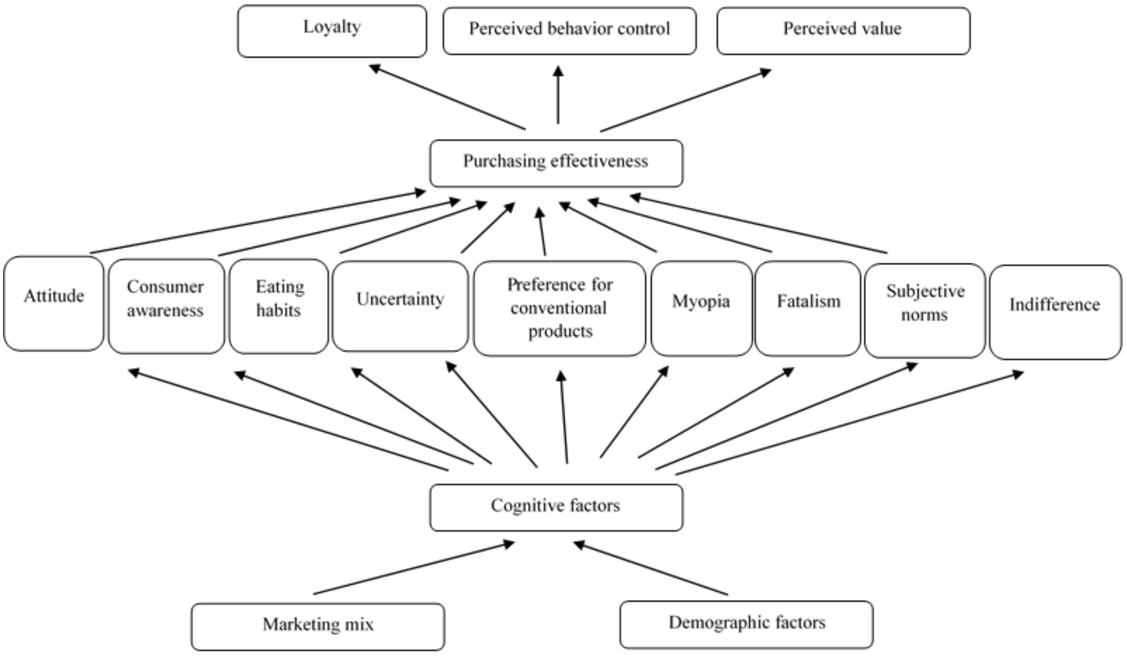

Figure 3- ISM modeling

MICMAC Analysis

By calculating the number of influencing factors in a row and column of the reachability matrix with matrix elements "1" and "1*", the value of driving power and dependence power of the influencing factors on Purchase Intention were obtained, as shown in Table 6.

The analysis of Intensity of Influence and Dependency (MICMAC) categorizes indicators based on their degrees of influence and dependence, as illustrated in Fig. 3. The attributes are grouped into four clusters:

- Autonomous Attributes: Low driving power and low dependence

- Dependent Attributes: High dependence but low driving power

- Linkage Attributes: High dependence and high driving power

- Driver/Independent Attributes: High driving power but low dependence.

The assessment results indicate that loyalty, perceived behavior control, perceived value, and purchasing effectiveness fall into cluster 2, showing high dependence but low driving power. Conversely, the Cognitive factors, marketing mix, and Demographic factors are in cluster 4, indicating strong influence but weak dependence. The remaining criteria are in cluster 3, demonstrating strong dependency and directing power in Figs. 3 and 4.

Fuzzy BWM-based criteria prioritization

This section uses the fuzzy Best-Worst Method (BWM) to establish the related weights and significance of the research factors. Drawing on the findings of the MICMAC analysis, Cluster 3 encompassed 9 criteria that demonstrated both strong abilities to influence other criteria and high susceptibility to being influenced by other criteria. Consequently, we determine the weights and ranks of these 9 criteria. To conduct the fuzzy BWM, the best and the worst criteria should be determined first. Based on the experts' point of view, the most important criterion is Awareness, while the least important criterion is Fatalism. The fuzzy preference degree of the best criteria to other criteria should be determined. To contrast the top-ranked criterion with the others and the lowest-ranked criterion with the others, we conducted pairwise comparisons referencing the spectrum of preferences in Table 1.

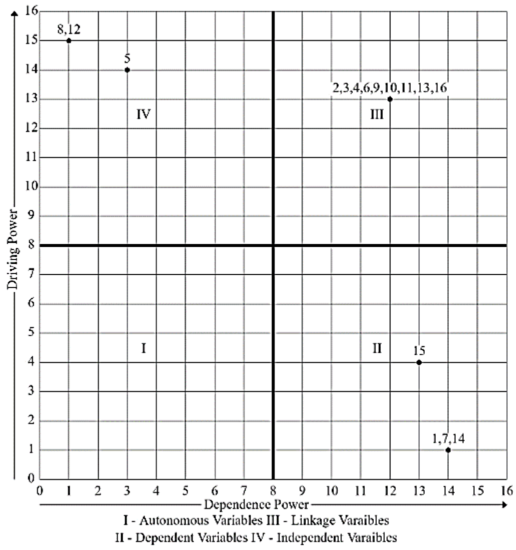

Figure 4- Driving power and dependence diagram

The information collected via the survey could be used to determine the fuzzy preference degree, however, as there are 10 experts to provide their opinions, it would be necessary to combine the judgments of different experts and obtain the comprehensive fuzzy preference degree by aggregating the judgments. To do this, we use the weighted average operator to calculate the aggregated fuzzy preference degree as:

$$\tilde{p} = \frac{1}{n}\sum_{i=1}^{n} \lambda_i \tilde{p}_i \tag{5}$$

Where n is the number of experts, in this case, n = 10, pi is the fuzzy preference degree provided by the ith expert, and ai is the weight of the ith expert with $0 \leq ai \leq 1$ and $\Sigma ni = 1\ \lambda i = 1$. As different experts have different backgrounds and experiences, we introduce a subjective weight calculation method for the experts:

$$\lambda_i = \frac{H_i}{\sum_{k=1}^{n} H_k} \tag{6}$$

Where Hi is the weight score of the ith expert, and is calculated according to Table 8.

Table 8- Expert weight calculation score

Aspect	Class	Score
Title	PhD	4
	Master's degree	3
	Bachelor's degree	2
	Associate	1
Experience	Over 20 years	4
	10–19 years	3
	5–9 years	2
	Under 5 years	1

By combining the judgments of all 10 experts, the fuzzy preference degree of the best criterion to other criteria could be obtained for all criteria and sub-criteria. Similarly, the fuzzy preference degree of other criteria to the worst criterion could be determined by combining the judgments of all 10 experts, and the others-to-worst vector could be obtained.

The weight represents the relative importance of a criterion; however, it should be noted that it represents the importance of the criterion over other ''related'' criteria, i.e., criteria in the same layer. Therefore, in this step, we obtain the weight of the criteria, that is, the relative weight of the criteria (Gao *et al*., 2023). Solving these pairwise comparisons is accomplished using Eq. (3) in Lingo software, resulting in the weights of the criteria, as presented in Table 9. Based on these weights, the measure of Awareness is the highest with 0.3837 as its weight. With a weight of 0.1199, the promotion of Attitude among consumers criterion earns the second position, followed by the Subjective norms criterion in third place with a weight of 0.0319.

Table 9- Wt. and Final ranking of the criteria

	Criterion	Crisp Weight	Rank
S_2	Awareness	0.3837	1
S_3	Eating habits	0.0599	6
S_4	Purchasing effectiveness	0.0799	4
S_6	Attitude	0.1199	2
S_9	Preference for conventional products	0.0799	4
S_{10}	Myopia	0.0799	4
S_{11}	Fatalism	0.0319	7
S_{13}	Subjective norms	0.0959	3
S_{16}	Indifference	0.0685	5

Conclusion

This study aimed to identify and prioritize the key factors influencing consumers' purchase intentions toward antibiotic-free poultry meat. By integrating Interpretive Structural Modeling (ISM), MICMAC analysis, and the fuzzy Best-Worst Method (BWM), we systematically identified, structured, and ranked the most relevant purchasing criteria based on their relative importance.

The ISM analysis revealed a hierarchical structure consisting of five levels. Marketing mix (S8) and demographic factors (S12) at the highest level demonstrated substantial driving power over cognitive factors (S5), which in turn shape attitudes, awareness, eating habits, and other behavioral responses. Lower-level factors, including loyalty, perceived value, and perceived behavioral control, were identified as outcomes rather than drivers, indicating that higher-level factors are critical determinants of purchase behavior. Overall, as one moves from higher to lower levels, driving power decreases while dependence increases, emphasizing the importance of targeting higher-level variables to effectively influence consumer decisions.

MICMAC analysis confirmed that none of the factors fell into the autonomous cluster. Demographic, marketing mix, and cognitive factors were classified as independent, exerting a strong influence over other variables. For instance, demographic characteristics such as low income, large household size, and limited education can negatively affect purchasing power, knowledge of healthy products, and consumer engagement during shopping, consistent with prior studies (Ziaei-Bideh & Namakshenas-Jahromi, 2019; Wojciechowska-Solis & Sorok, 2017).

Fuzzy BWM results highlighted "awareness" as the top-ranked criterion with a weight of 0.3837, demonstrating its central role in connecting and influencing other factors. Enhancing consumer awareness of the benefits and potential risks of antibiotic-free poultry can significantly improve decision-making, foster positive behavioral changes, and strengthen the impact of marketing and policy interventions. Therefore, strategies aiming to promote purchase intentions should prioritize awareness enhancement as a foundational step.

Based on the findings, policymakers and marketers should adopt an integrated approach to enhance consumers' purchase intentions toward antibiotic-free poultry. This includes designing awareness campaigns and educational initiatives to increase knowledge of the benefits and safety of such products, implementing targeted marketing strategies that focus on higher-level cognitive and demographic drivers, and providing incentives or subsidies to improve accessibility for low-income or less-educated consumers. Additionally, enhancing trust and transparency through clear labeling, certifications, and traceability systems can reinforce positive purchase behavior. Combining these marketing, educational, and regulatory measures in a coordinated manner is expected to maximize the effectiveness of interventions and promote sustainable adoption of antibiotic-free poultry. This study contributes to the literature on consumer behavior by providing a structured and prioritized understanding of the determinants of purchase intention. The methodological integration of ISM, MICMAC, and fuzzy BWM offers a novel approach for analyzing complex decision-making processes in the context of healthy and sustainable food consumption.

Nevertheless, the study has limitations. First, the identified factors primarily relied on expert judgment and grounded theory, which may limit generalizability. Second, the prioritization process involved a relatively small group of experts, which could constrain the broader applicability of the results. Future research could address these limitations by expanding the expert panel, incorporating consumer survey data, applying longitudinal designs, or extending the analysis to other food categories. Such efforts would further validate and generalize the findings presented here.

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شناسایی و طبقه‌بندی عوامل مؤثر بر قصد خرید مصرف‌کنندگان نسبت به مرغ بدون آنتی‌بیوتیک: شواهدی از مشهد، ایران

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چکیده

تولید طیور یکی از سریع‌ترین صنایع در حال رشد در جهان به‌شمار می‌رود و به‌عنوان منبع اصلی تأمین گوشت عمل می‌کند. برای دستیابی به رشد حداکثری در حداقل زمان، تولیدکنندگان اغلب از آنتی‌بیوتیک‌ها به‌عنوان پیشگیری‌کننده بیماری و محرک رشد استفاده می‌کنند. با این حال، در مطالعات متعددی جهانی، بقایای آنتی‌بیوتیک در گوشت طیور شناسایی شده است که نگرانی‌هایی را درباره توسعه بالقوه مقاومت ضدمیکروبی در عوامل بیماری‌زای انسانی ایجاد می‌کند. در نتیجه، تقاضای برای محصولات غذایی سالم‌تر، از جمله طیور بدون آنتی‌بیوتیک، رو به افزایش است. در حالی‌که این روند در سطح جهانی گسترش‌یافته، در ایران هنوز در مراحل اولیه قرار دارد. بر این اساس، شناسایی عوامل مؤثر بر الگوهای مصرف خانوار نخستین گام اساسی برای توسعه بازار محصولات سالم محسوب می‌شود. در این مطالعه ترکیبی از سه ابزار تصمیم‌گیری شامل مدل‌سازی ساختاری تفسیری، تحلیل میک‌مک و روش بهترین-بدترین فازی برای ارزیابی عوامل مؤثر بر خرید مرغ بدون آنتی‌بیوتیک در شهر مشهد به‌کار گرفته شده است؛ بازاری کلیدی که چنین محصولاتی در آن عرضه می‌شود و رفتار مصرف‌کننده در آن در حال شکل‌گیری است. فرآیند تحقیق با مدل‌سازی ساختاری تفسیری آغاز می‌شود که مدلی سلسله مراتبی از روابط تأثیر و وابستگی متقابل میان عوامل ترسیم می‌کند. این مرحله در درک اثر جمعی متغیرها بر قصد خرید مصرف‌کننده نقش بنیادین دارد. در ادامه، تحلیل میک‌مک این عوامل را بر اساس میزان تأثیر و وابستگی طبقه‌بندی کرده و عناصر کلیدی مؤثر بر مزیت رقابتی را شناسایی می‌کند. در نهایت، روش بهترین-بدترین فازی برای وزن‌دهی این عوامل کلیدی به‌کار می‌رود. نتایج نشان می‌دهد که آگاهی مصرف‌کننده بالاترین وزن را دارد و پس از آن نگرش و هنجارهای ذهنی قرار می‌گیرند. شناسایی این عوامل و روابط متقابل آن‌ها، بینش‌های کاربردی ارزشمندی برای تصمیم‌گیرندگان و ذینفعان در زمینه برنامه‌ریزی استراتژیک و تعیین اولویت‌ها فراهم می‌کند. بر اساس این یافته‌ها، توصیه می‌شود که سیاست‌گذاران و بازاریابان بر افزایش آگاهی مصرف‌کنندگان، شکل‌دهی نگرش‌های مثبت و بهره‌گیری از هنجارهای ذهنی برای تشویق به خرید مرغ بدون آنتی‌بیوتیک تمرکز کنند. اجرای کمپین‌های آموزشی هدفمند، استفاده از برچسب‌گذاری آموزنده و طراحی استراتژی‌های بازاریابی متناسب با ترجیحات مصرف‌کننده می‌تواند به افزایش پذیرش و حمایت از الگوهای مصرف سالم‌تر کمک کند.

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Formulating Adaptation Policy Strategies to Enhance Resilience under Climate Change (Case Study: Agriculture Zayandeh Rud Basin)

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Abstract

Climate change, with its gradual and complex impacts, has increasingly inflicted damages on the agricultural sector of arid and semi-arid regions in Iran, including the Zayandeh-Rud Basin. This study aims to develop strategic adaptation policies to enhance agricultural resilience in response to climate change in this basin. The research is based on the Sendai Framework for Disaster Risk Reduction (SFDRR) and the resilience criteria established by the World Economic Forum (2013). A descriptive-analytical methodology was employed, combining documentary studies, field surveys, and the Delphi policy method to achieve expert consensus. Purposive sampling targeted faculties, agricultural experts of the Ministry of Agriculture, as well as producers and exporters of agricultural products with substantial expertise in Climate change issues, adaptation policies, and resilience. Data collection instruments consisted of four structured questionnaires designed to identify strengths and weaknesses, weight resilience criteria ,prioritize policies, and select strategies, complemented by semi-structured interviews. Initially, to determine the strategic position of agriculture in the Zayandeh-Rud Basin, Internal Factor Evaluation (IFE), External Factor Evaluation (EFE), and Internal-External (IE) matrices were utilized. Subsequently, the Analytic Hierarchy Process (AHP) and the multi-criteria decision-making PROMETHEE method were employed to prioritize adaptation policies aimed at enhancing resilience to Climate Change. Suitable strategies were developed and extracted through SWOT analysis, and finally, the Quantitative Strategic Planning Matrix (QSPM) was used to evaluate the relative attractiveness and feasibility of each strategy, thereby selecting the implementable final policies. Findings indicated that agriculture in the Zayandeh-Rud Basin, with a final internal factor score of 2.04 and external factor score of 2.12, is in defensive position (survival mode) and exhibits low resilience due to water transfer and scarcity, land fragmentation and subsidence, and weaknesses in modern infrastructure. The most attractive adaptation policies identified under the defensive strategy include equitable water distribution (Total Attractiveness Score (TAS=1.46), development-oriented water resource planning (TAS=1.38), optimization of water. consumption and reduction of losses (TAS=1.35), control of groundwater levels (TAS=1.23), reform of regulations related to land fragmentation (TAS=1.18), and farmer participation in water resource management (TAS=1.16). The proposed solutions emphasize strengthening integrated and basin-based water governance, implementing participatory strategic management models, investing in modern and soft technologies, gradually revising water-related laws and regulations, and expanding research and national strategy formulation. The results of this study provide actionable, stakeholder-inclusive recommendations for policymakers to enhance sustainability and resilience in vulnerable agricultural regions.

Keywords: Adaptation policy, Agricultural resilience strategies, Participatory governance, Strategic planning

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Introduction

Agricultural economies worldwide face numerous risks, among which climate change has emerged as one of the most significant challenges in recent decades. According to the Intergovernmental Panel on climate change (IPCC[1]), climate change refers to irreversible alterations in the climate of a region, distinguished from short-term weather fluctuations, arising from both anthropogenic activities and natural variability (IPCC, 2022). The consequences of climate change-including increased frequency and intensity of extreme events, droughts, floods, and rising temperatures- have led to decreased agricultural productivity, food insecurity, economic losses, and heightened environmental instability (Bhatasara & Nyamwanza, 2018).

Due to its geographical location, Iran is highly vulnerable to climate change impacts. The Zayandeh-Rud Basin, spanning 26,917 square kilometers with approximately 120,000 hectares under cultivation, annually produces over 2 million tons of crop and horticultural products and provides direct employment for more than 172,000 agricultural workers. This region ranks first nationwide in onion and seed potato tuber production and holds prominent positions in safflower and melon cultivation (Isfahan Agricultural Jihad Organization, 2023). Nevertheless, it faces significant challenges such as declining water resources, land subsidence, and escalating competition for water among agricultural, industrial, and urban sectors. The drying up of the Zayandeh-Rud river, recurrent droughts, and unsustainable water resource management have exacerbated the region's socio-economic and environmental crises (Safavi *et al.*, 2015; Teymouri *et al.*, 2023).

In response to these challenges, researchers, planners, and policymakers emphasize the importance of disaster risk reduction, enhancing agricultural resilience, and formulating climate adaptation policies tailored to local conditions. They seek to develop appropriate strategies based on various approaches and models to mitigate the economic damages caused by climate variability. Within disaster risk management literature, one pivotal approach focuses on strengthening existing community capacities to empower vulnerable local populations to better prepare for, cope with, and recover from adverse climate impacts—the resilience strategy (Scherzer *et al.*, 2019). Resilience is defined as the ability of social and economic systems to absorb disturbances, adapt to new conditions, and recover from climatic shocks while maintaining core functions (*Scherzer et al.*, 2019; Adger, 2000). According to this strategy, social subsystems, governance, technology, and environment must be designed to absorb both internal and external risks, adapt to highly variable conditions, and simultaneously sustain system stability and performance (World Economic Forum, 2013). Such adaptations—whether anticipatory, planned, or long-term response strategies—are implemented prior to events and, due to their broad nature, are commonly regarded as governmental responsibilities (Bandyopadhyay *et al.*, 2011).

Governments should employ comprehensive and inclusive strategy formulation to outline how policies can achieve missions and objectives given contextual conditions. Strategy formulation is a critical component of adapting to natural and social hazards (Saraei & Shamsiri, 2013). In other words, policymakers must first understand the Strengths, Weaknesses, Opportunities, and Threats (SWOT) within the system, then prioritize compatible policies (PROMETHEE[2]) to adopt suitable strategies (QSPM[3]) aimed at enhancing resilience.

Recent studies in Iran have demonstrated that multiple factors, such as the development of agricultural insurance, establishment of

1- Intergovernmental Panel on Climate Change

2- Preference Ranking Organization Method for Enrichment Evaluation

3- Quantitative Strategic Planning Matrix drought monitoring and early warning systems, and incorporation of indigenous knowledge, play key roles in boosting farmers' resilience (Sadeghloo *et al*., 2014; Khakifirouz *et al*., 2022). Moreover, research using multi-criteria decision-making methods like VIKOR, PROMETHEE-AHP, TOPSIS, and ANP have focused on prioritizing policies and identifying the most effective adaptation strategies (Dehghanpour *et al*., 2020a; *Dehghanpour et al*., 2020b; Ehsani *et al*., 2021).

At the macro level, studies employing strategic models such as SWOT-QSPM have shown that defensive strategies, water consumption management, mechanization development, and economic diversification are among the most significant policy recommendations for enhancing agricultural resilience and sustainability in Iran's vulnerable regions (Sadeghi *et al*., 2019; Ghasemi *et al*., 2020). Furthermore, research highlights the importance of institutional policies and reforms in water governance processes, especially in critical areas like the Zayandeh-Rud watershed (Safavi & Afshar, 2006; Yadegari *et al*., 2018; Madani, 2014).

Despite these efforts, substantial gaps remain in developing comprehensive and localized models for assessing and improving agricultural resilience at the watershed scale. Particularly, aligning adaptation policies with the Sendai Framework for Disaster Risk Reduction (SFDRR), the resilience criteria of the World. Economic Forum, and the utilization of integrated multi-criteria decision-making approaches can assist policymakers in designing more effective strategies to confront Climate Change.

Accordingly, this study aims to identify and prioritize adaptation policies to enhance agricultural resilience in the Zayandeh-Rud watershed and to formulate actionable strategies based on these policies using advanced multi-criteria decision-making and strategic analysis approaches. By leveraging the experiences and findings of previous research, this study seeks to provide a scientific and practical framework for policymaking and sustainable agricultural development planning in Iran's vulnerable areas. Ultimately, the research intends to fill the existing scholarly gap through the identification, formulation, prioritization, and analysis of adaptation policies to increase agricultural resilience in the Zayandeh-Rud Basin, aligned with the SFDRR, the World Economic Forum's resilience criteria and stakeholder participation.

Materials and Methods

This research was conducted with a descriptive-analytical and applied approach, employing both qualitative and quantitative methods. The study was based on the Sendai Framework for Disaster Risk Reduction 2015–2030 (UNDRR, 2015) and the resilience criteria of the World Economic Forum (World Economic Forum, 2013) to perform a comprehensive assessment of agricultural resilience and adaptation policies. Additionally, economic resilience models for farmers and the Delphi technique for expert consensus were utilized, emphasizing both quantitative and qualitative indicators to enable a multidimensional analysis of the capacities and constraints of the agricultural sector in confronting Climate Change. In this context, the "Comprehensive Strategic Management Model" (illustrated in Fig. 1) was applied to identify optimal strategies for strengthening the prescriptive resilience paradigm of agriculture in the Zayandeh-Rud Basin. This model encompasses three main stages: strategy formulation, implementation, and evaluation.

Given that the primary objective of this research is to formulate adaptation policy strategies to enhance Climate change resilience in the agriculture of the Zayandeh-Rud Basin—and that. Policy implementation depends on subsequent governmental approval and executive actions—only the first stage of the Comprehensive Strategic Management Model, namely strategy formulation, was examined in this study.

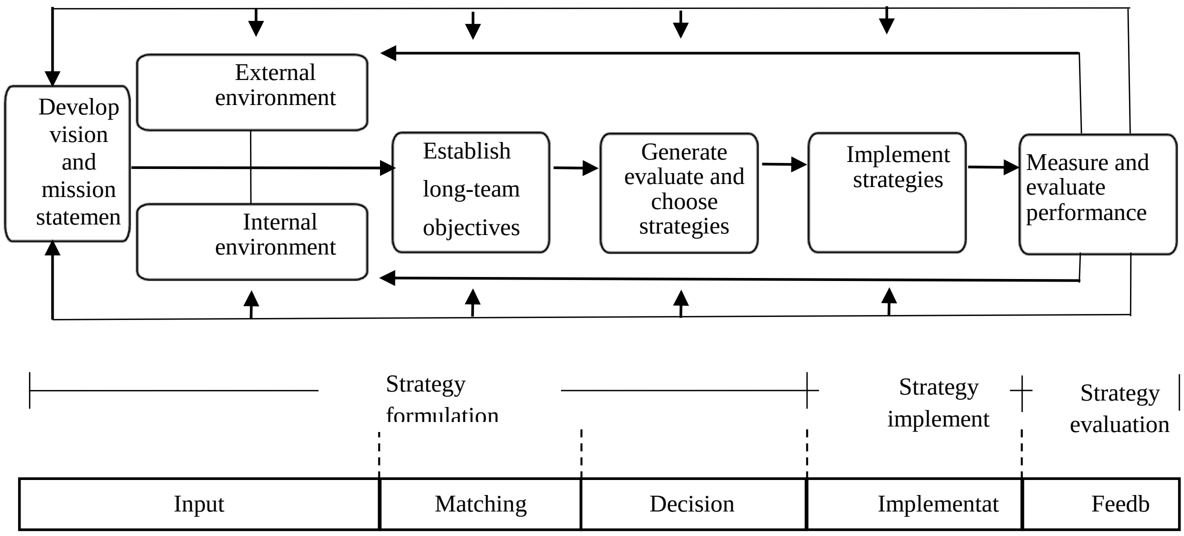


Figure 1– The comprehensive strategic management model (David & David, 2017; Moradi, 2011)

The main techniques for strategy formulation can be integrated into a three-stage framework consisting of the input stage, matching stage, and decision-making stage. This research followed the Comprehensive Strategic Management Model (David & David, 2017) sequentially and iteratively, such that the output of each stage (internal and external. factor analysis via the IFE and EFE matrices) served as the input to the next stage (strategic positioning via the IE matrix and SWOT analysis). Subsequently, adaptation policies were prioritized using the Analytic Hierarchy Process (AHP) and PROMETHEE methods and evaluated for attractiveness and selection using the Quantitative Strategic Planning Matrix (QSPM). This staged structure ensures theoretical and practical coherence, providing a logical transition from situational analysis to strategic decision-making. The stages and corresponding tools are depicted in Fig. 2.

	Stage one: Input stage		
Internal factor evaluation (IFE) matrix			**External factor evaluation (EFE) matrix**
	Stage two: Matching stage		
Internal-external (IE) matrix	Analytic hierarchy process (AHP)	PROMETHEE method	SWOT matrix
	Stage three: Decision-making phase		
	Quantitative strategic planning matrix (QSPM)		

Figure 2– The stages of strategy formulation (David & David, 2017)

Stage One: Input Stage

The first stage summarizes the initial input data necessary for strategy formulation. This includes the External Factor Evaluation (EFE) and Internal Factor Evaluation (IFE) matrices. The EFE and IFE matrices are tools used to analyze the strengths, weaknesses, opportunities, and threats (SWOT) of an economic sector. The development of these two matrices involves five steps:

1. Identifying and listing key external and internal factors (including strengths, weaknesses, opportunities, and threats) through document review and expert judgment.
2. Weighting each factor according to its relative importance: each factor is initially scored from 1 to 10, then normalized so that the total weights sum to one.
3. Ranking each factor on a scale from 1 to 4 (4 = excellent strength/opportunity, 3 =

average strength/opportunity, 2 = average weakness/threat, 1 = critical weakness/threat).

4. Calculating the final score for each factor by multiplying its weight by its rank.
5. Summing the final weighted scores to obtain overall internal and external factor scores (David & David, 2017).

Stage Two: Matching Stage

The second stage seeks to align internal strengths and weaknesses with external opportunities and threats. This involves the Internal-External (IE) matrix, weight determination of criteria using Analytic Hierarchy Process (AHP), the PROMETHEE method, and SWOT analysis (David & David, 2017).

To analyze internal and external factors simultaneously, the IE matrix places scores from the IFE and EFE matrices along the horizontal and vertical. Axes to determine the strategic position of the economic sector and select the appropriate strategy (Saraei & Shamsiri, 2013; David & David, 2017).

Policy option prioritization can employ various approaches; one prominent method is Multi-Criteria Decision Making (MCDM), suitable for ranking policy options. As this research aims to prioritize adaptation policies, the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) was applied. PROMETHEE is a non-compensatory, preference-based model favored for its simplicity, transparency, interpretability, and ability to handle incomparable alternatives, distinguishing it from scoring methods such as TOPSIS and compromise methods like VIKOR. Moreover, the AHP technique was combined with PROMETHEE solely to weight criteria based on pairwise comparisons.

Following the identification of adaptation policies and weighting of resilience criteria through AHP, policy prioritization was conducted using PROMETHEE. Rankings were presented as PROMETHEE II complete rankings based on the net flow (Phi), derived from the positive (Phi+) and negative (Phi−) flows. The degree of preference of option a over option b, denoted π (a, b), is calculated by:

$$\pi(a.b) = \sum_{j=1}^{k} wjpj\,(a.b).[\sum_{j=1}^{k} wj = 1] \qquad (1)$$

In relation (1), wj*wj* (for j=1,2, …, n*j*=1,2, …, *n*) represents the normalized weight of each criterion. To calculate the overall preference strength of option a*a* compared to other options, the leaving flow (positive outranking flow) is computed using Equation (2). This flow indicates how much option a*a* is preferred over others and reflects its strength (the maximum positive flow ϕ^{+} (a) corresponds to the best choice).

The preference degree of other options over option a*a*, called the entering flow (negative outranking flow), can be calculated using Equation (3). This flow shows the preference of others over option a*a* (the smallest negative flow ϕ^{-} (a) indicates the best option).

The positive ranking flow or leaving flow is expressed by:

$$\emptyset^{+}(a) = \frac{1}{n-1}\sum_{x\epsilon A}\pi(a.x) \qquad (2)$$

The negative ranking flow or entering flow is given by:

$$\emptyset^{-}(a) = \frac{1}{n-1}\sum_{x\epsilon A}\pi(a.x) \qquad (3)$$

With these flows, the available options can be compared to select the best one. The partial ranking, PROMETHEE I, is performed by separately evaluating the two flows ϕ^{+} (a) and ϕ^{-} (a). For a complete ranking of options, PROMETHEE II calculates the net flow for each option as shown in Equation (4):

$$\emptyset(a) = \emptyset^{+}(a) - \emptyset^{-}(a) \qquad (4)$$

PROMETHEE II refers to the complete ranking based on this net flow (Amiri *et al.*, 2017).

SWOT[1] analysis is a critical tool used to align internal strengths and weaknesses within the economic sector with external opportunities and threats. It provides a systematic analysis to determine policies and formulate strategies that create optimal fit among these factors. Based on this balance, four types of strategies can be identified: SO (Strength-Opportunity), WO (Weakness-

1- Strength-Weaknesses-Opportunities-Threats

Opportunity), ST (Strength-Threat), and WT (Weakness-Threat) (David & David, 2017).

Stage Three: Decision-Making Phase

The third phase assists in strategy formulation decision-making, enabling planners and policymakers to use inputs from Stage One to objectively evaluate the strategies identified in Stage Two, showing the relative attractiveness of alternative strategies. This stage employs a single technique, the Quantitative Strategic Planning Matrix (QSPM), which involves the following six steps:

1. List strengths, opportunities, and threats in the first column.
2. Input weighted scores from the internal and external factor matrices in the second column.
3. Place the SWOT matrix at the top row of the QSPM.
4. Determine the attractiveness coefficient using a Likert scale (ranging from “should not be implemented” to “definitely should be implemented”).
5. Calculate scores by multiplying importance weights by attractiveness coefficients.
6. Sum scores for each column to indicate the attractiveness of each strategy (David & David, 2017).

Data were collected through document review, field surveys, and semi-structured interviews with key stakeholders, including government officials, private sector actors, and experienced farmers in the Zayandeh-Rud Basin. Purposive sampling with an expert approach was applied to select individuals with relevant expertise and experience regarding agricultural resilience and Climate change adaptation policies in the basin. The panel consisted of 29 experts from the Agricultural Jihad Organization and 20 producers and exporters of agricultural products, selected in collaboration with the provincial Agricultural Jihad, based on criteria such as a minimum of 10 years of related work experience and recognized academic qualifications. In other words, a credentialed approach was used for panel member selection, identifying individuals aware of specific policy issues.

A structured questionnaire, developed based on prior studies and expert consultation, covered internal and external factors influencing agricultural resilience and potential adaptation policies.

To enhance data validity and comprehensiveness, stakeholder and expert selection followed scientific and practical criteria. Agricultural Jihad experts were chosen for their key role in policymaking, implementation, and technology transfer; lead farmers and producers for their practical experience and field awareness; exporters as vital links in markets and production; and university professors and researchers for their specialized knowledge and analytical capability. This stakeholder combination was aimed at reflecting expert, experiential, and market-oriented perspectives, thus improving research quality and credibility.

An analysis of the power, influence, and interests of these groups showed farmers as the most vulnerable and influential stakeholders due to high livelihood dependence on water and soil resources and exposure to Climate change impacts. Agricultural Jihad experts, as main policymakers and executors, play a pivotal role in resource management and the success of adaptation policies. Exporters are key to economic sustainability and market development, while academics enhance policy credibility through scientific analysis and innovative solutions.

This approach, aligned with international standards and comparable studies, increased the precision, validity, and applicability of the research findings.

Table 1 provides the analysis of power, influence, and interests of the key stakeholders involved in the study.

Table 1 -Analysis of power, influence, and interests of key stakeholders participating in the study

Rationale for selection and role in the study	Key interests	Power/Influence in policy-making	Stakeholder group
Main policy-makers and implementers; possess regional expertise and executive experience	Enhancing agricultural resilience, safeguarding farmers'	High	Agricultural Jihad Organization Experts
Primary beneficiaries; practical and market experience; represent real field and market challenges	Securing water, income stability, production sustainability, market development, export sustainability	Moderate to High	Leading Farmers and Agricultural Product Exporters
Provide scientific solutions, policy analysis, and knowledge transfer	Sustainable development, technology transfer, education	Moderate	University Professors and Researchers

Source: Research results

Results and Discussion

This section analyzes the collected data to achieve the research objectives through three main stages: (1) determining the strategic position of agriculture in the Zayandeh-Rud Basin, (2) prioritizing adaptation policies to enhance resilience to climate change, and (3) formulating strategies for implementing these adaptive policies within the basin.

Stage One: Determining the Strategic Position of Agriculture in the Zayandeh-Rud Basin

Strategic positioning of agriculture is a process whereby agricultural planners and policymakers conduct a thorough analysis of internal factors (strengths and weaknesses) and external factors (opportunities and threats) to develop suitable strategies for improving agricultural productivity and performance.

Internal Factors Analysis (Strengths and Weaknesses)

In this stage, a total of 43 internal factors (strengths and weaknesses) were identified through documentary research. According to the aggregated perspectives of experts from the Agricultural Jihad Organization of Isfahan province and county (government agents) and agricultural stakeholders in the Zayandeh-Rud Basin, there are 20 identified strengths and 23 weaknesses in the basin's agriculture.

The prioritization of internal factors was based on final scoring. The primary strengths, in order of importance, include: the existence of markets, support services and transportation infrastructure, warehouses, reservoirs, cold storage facilities, and agro-processing industries within the basin's agricultural supply chain; crop diversity; and the degree of implementation of modern water and irrigation technologies.

The main weaknesses, ranked by significance, are: fragmented and small farm plots, low utilization of renewable energy sources, and inadequate transfer of agricultural technologies (such as robotics and smart farming) to farmers in the Zayandeh-Rud agricultural sector. These factors are listed in detail in Table 2.

External Factors Analysis (Opportunities and Threats)

In this stage, 28 external factors (opportunities and threats) were identified through documentary research. Based on the aggregated views of experts from the Agricultural Jihad Organization of Isfahan province and county (government agents), it was determined that agriculture in the Zayandeh-Rud Basin faces 9 opportunities and 19 threats related to Climate Change.

The most significant opportunities, in order of importance, include: integrated water resources management in the Zayandeh-Rud Basin, proximity to major national markets (due to the basin's central location in the country), guaranteed water rights for farmers, environmental protection, and the sustainability of the Zayandeh-Rud river flow (fair water distribution).

The major threats, ranked by their significance, comprise: water transfer to other basins and industrial development exceeding the basin's capacity, agricultural land subsidence, and intensified inter-sectoral and inter-provincial competition for water resources under changing climatic conditions. These factors are detailed in Table 3, where opportunities and threats were identified by experts and presented without alterations.

Table 2- Internal factor evaluation (IFE) matrix

Code	Internal factors	(1-10) Importance	Weight	(1-4) Rating	Final score
	Strengths				
S_1	Existence of markets, support services, transportation, warehouses, silos, cold storages, and agro-processing industries in the Zayandeh-Rud Basin (agricultural supply chain)	6.76	0.025	3	0.075
S_2	Crop diversity	6.31	0.023	3	0.07
S_3	Deployment of modern water and irrigation systems and technologies in the basin	6.24	0.023	3	0.069
S_4	Efficiency of agricultural water storage, transfer, and distribution networks	6.14	0.023	3	0.068
S_5	Degree of alignment and compliance between adaptation policies and the national development plan	6.10	0.023	3	0.068
S_6	Profitability of agricultural products	6.03	0.022	3	0.067
S_7	Awareness and attitudes of officials, experts, and producers regarding climate change and resilience/adaptation strategies	6.03	0.022	3	0.067
S_8	Level of farmers’ knowledge and awareness about climate change	6.03	0.022	3	0.067
S_9	Production of crops adapted to the basin’s climatic conditions	5.93	0.022	3	0.066
S_{10}	Number of producers cultivating resilient and adapted plant species	5.92	0.022	3	0.066
S_{11}	Cultivation of halophyte (salt-tolerant) plants	5.90	0.022	3	0.065
S_{12}	Development and improvement of agricultural production units (poultry, livestock, etc.)	5.86	0.022	3	0.065
S_{13}	Level of interaction between management sectors and agricultural stakeholders	5.86	0.022	3	0.065
S_{14}	Existence of programs, regulations, and facilities for controlling and monitoring production resources	5.86	0.022	3	0.065
S_{15}	Pricing and guaranteed purchase of resilient and adapted products (e.g., safflower)	5.83	0.022	3	0.065
S_{16}	Technical and professional management capacities of individuals and institutions in the agricultural sector to address climate change	5.83	0.022	3	0.065
S_{17}	Utilization of public capacities and professional associations in achieving program objectives	5.76	0.021	3	0.064
S_{18}	High mechanization capacity	5.72	0.021	3	0.063
S_{19}	Controlled-environment agriculture (greenhouses, indoor, vertical, or protected farming)	5.61	0.021	3	0.062
S_{20}	Development of sustainable and climate-resilient agriculture	5.52	0.02	3	0.061
	Weaknesses				
W_1	Land fragmentation and small plot sizes	8.23	0.03	2	0.061
W_2	Lack of utilization of renewable energies	7.76	0.029	2	0.057
W_3	Lack of Transfer of agricultural technologies to farmers (robotics, smart farming, etc.)	7.55	0.028	2	0.056
W_4	Lack of Application of smart and precision agriculture	7.52	0.028	2	0.056
W_5	Lack of development of modern, smart, and precision agricultural technologies	6.45	0.024	2	0.048
W_6	Lack of Coordination and collaboration among responsible agencies in climate change adaptation, prioritizing objectives and resources	6.17	0.023	2	0.046
W_7	Low water use efficiency and weak protection of basin water resources	7.14	0.026	1	0.026
W_8	Limited Access to financial markets (e.g., farmer income stabilization funds)	6.86	0.025	1	0.025
W_9	Low Farmers’ education and literacy level	6.79	0.025	1	0.025
W_{10}	Lack of Adoption of modern technologies by farmers	6.72	0.025	1	0.025
W_{11}	Poor Status of agricultural knowledge-based companies	6.55	0.024	1	0.024
W_{12}	Insufficient Cultivation of crops compatible with sustainable development and environmental protection	6.45	0.024	1	0.024
W_{13}	Insufficient Agricultural and retirement insurance coverage for farmers	6.38	0.024	1	0.024
W_{14}	Lack of Existence of a comprehensive agricultural information database in the basin	6.38	0.024	1	0.024
W_{15}	Low Level of best farming practices (quality and yield)	6.21	0.023	1	0.023
W_{16}	Low Degree of knowledge and information sharing on climate-smart agricultural technologies and methods by relevant institutions	6.17	0.023	1	0.023
W_{17}	Low Farmers’ income diversification (integrated farming, home-based businesses, etc.)	6.14	0.023	1	0.023
W_{18}	Lack of Compliance with optimal cropping patterns	6.07	0.022	1	0.022
W_{19}	Land productivity	6.03	0.022	1	0.022
W_{20}	Lack of Existence of producer cooperatives, marketplaces, and direct sales stations in the basin	6.00	0.022	1	0.022
W_{21}	Lack of Optimal use of production resources	5.90	0.022	1	0.022
W_{22}	Inadequate Soil tillage methods and poor soil conservation practices	5.83	0.022	1	0.022
W_{23}	Lack of Access to agricultural infrastructure (technologies, etc.)	5.79	0.021	1	0.021
	Total Internal Factor Analysis Score	270.44	1		2.0437

Source: Research results

Table 3- External Factor Evaluation (EFE) Matrix

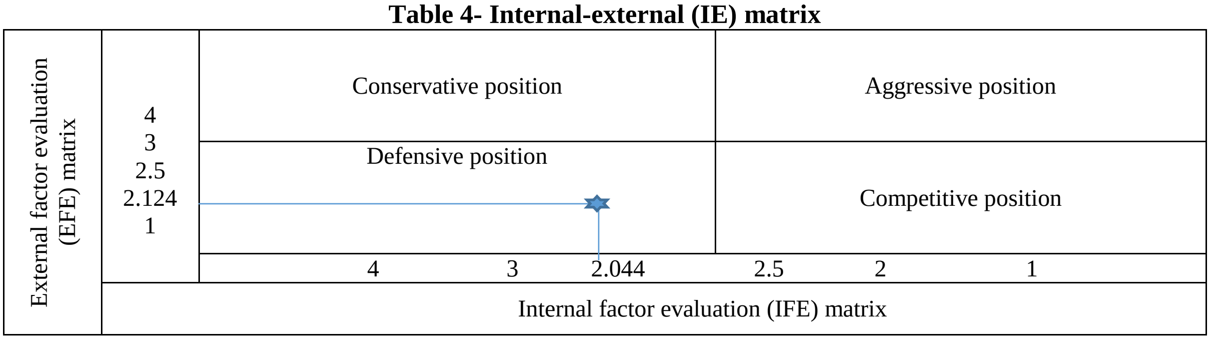
Code	External factors	(1-10) Importance	Weight	Rating	Final score
	Opportunities				
O_1	Integrated water resources management in the Zayandeh-Rud Basin	7.83	0.038	4	0.153
O_2	Proximity to major national markets (central location in the country)	7.62	0.037	4	0.149
O_3	Securing water rights for farmers, the environment, and the sustainability of the Zayandeh-Rud River (equitable water distribution)	7.6	0.037	4	0.148
O_4	Active human and social capital in the agricultural sector	7.31	0.036	4	0.143
O_5	Existence of programs, regulations, and facilities for controlling and monitoring basin resources	6.79	0.033	4	0.133
O_6	Natural and historical capital in the basin	7.46	0.036	3	0.109
O_7	Research and scientific infrastructure in the basin (universities, research centers, etc.)	6.21	0.03	3	0.091
O_8	Infrastructure and facilities for agricultural exports (customs, etc.)	6.17	0.03	3	0.09
O_9	Presence of unconventional water resources in the basin	6.1	0.03	3	0.089
	Threats				
T_1	Inter-basin water transfer and industrial development exceeding basin capacity	9.08	0.044	2	0.089
T_2	Land subsidence in agricultural areas	8.93	0.044	2	0.087
T_3	Intensified inter-sectoral and inter-provincial competition over water resources due to climate change	8.62	0.042	2	0.084
T_4	Decline in resources and increased pressure on basic resources under climate change	8.48	0.041	2	0.083
T_5	Intensified land use change and increased land value due to climate change	8.28	0.04	2	0.081
T_6	Escalation of conflicts, disputes, and social unrest among provinces in the Zayandeh-Rud Basin under climate change	8.24	0.04	2	0.08
T_7	Decrease in quantity (volume) and quality (standards and characteristics) of surface and groundwater due to climate change	7.93	0.039	2	0.077
T_8	Intensified soil erosion, dust storms, and increased soil salinity under climate change	7.28	0.036	2	0.071
T_9	Exit from agriculture and reduced investment in the sector	8.69	0.042	1	0.042
T_{10}	Reduced production, increased vulnerability, and economic difficulties for farmers under climate change	7.9	0.039	1	0.039
T_{11}	Increased frequency of natural disasters such as floods, fires, frost, droughts, heatwaves, hail, storms, dust storms, and untimely rains due to climate change	7.86	0.038	1	0.038
T_{12}	Declining resources, reduced productivity, and intensified price and market fluctuations under climate change (increased production costs in the basin)	7.5	0.037	1	0.037
T_{13}	Decline in quantity (amount of various elements) and quality (physical, chemical, and biological properties) of soil under climate change	7.31	0.036	1	0.036
T_{14}	Changes in rainfall timing, temperature fluctuations, and differences in precipitation patterns in the basin under climate change	6.97	0.034	1	0.034
T_{15}	Price fluctuations of agricultural products (food security, etc.)	6	0.029	1	0.029
T_{16}	Attention to agricultural biodiversity in the basin	5.9	0.029	1	0.029
T_{17}	Intensification of chemical fertilizer and pesticide use and Declining biodiversity by farmers	5.86	0.029	1	0.029
T_{18}	Outbreak of plant pests and diseases due to climate change	5.62	0.027	1	0.027
T_{19}	Balance between agricultural production and environmental protection	5.41	0.026	1	0.026
	Total External Factor Analysis Score	204	1		2.123

Source: Research results

Internal-External Factors Analysis (Strategic Position)

Based on the final scores of internal factors (2.04) and external factors (2.12) presented in Table 4, the strategic position of agriculture in the Zayandeh-Rud Basin was determined to be in a defensive (survival) posture .

Table 4- Internal-external (IE) matrix



Source: Research results

Stage Two: Prioritization of Adaptation Policies to Enhance Climate change Resilience

After designing the questionnaire based on Saaty's 9-point scale, weighting of resilience criteria was carried out by four professors from the Agricultural Economics Department at the University of Tehran and two experts from the Agricultural Jihad Organization of Isfahan province (government agents). Purposeful sampling was used to select the expert group for accurate and professional judgment in weighting the criteria. The experts were chosen based on their practical experience and theoretical knowledge relevant to the study.

The Analytic Hierarchy Process (AHP) and Expert Choice software were employed to assign weights to the resilience criteria. The inconsistency ratio for each pairwise comparison set, obtained via Expert Choice software, was 0.091, indicating an acceptable level of consistency in the findings.

According to the results of the criteria comparisons shown in Table 5, the redundancy dimension received the highest weight with 33%, as rated by the experts. It was followed by the responsiveness dimension (reaction capacity) with 31%, the self-organization dimension with 20%, the governance dimension with 12%, and finally, the robustness dimension with 4%, ranking them respectively in terms of their contribution to enhancing the resilience of adaptation policies.

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Table 5- Percentage importance of resilience criteria

Rank	Percentage importance	Criterion
2	0.309	Response
1	0.33	Redundancy
3	0.198	Recovery
4	0.119	Resourcefulness
5	0.044	Robustness

Source: Research results

In the context of formulating Climate change adaptation policies for the agricultural sector in the Zayandeh-Rud Basin, a comprehensive set of strategies, general policies, and adaptation tools were designed and implemented. Their main foundation was Iran’s Climate change Strategic Plan (2017) and the international Sendai Framework for Disaster Risk Reduction (SFDRR). These policies were developed using an integrated approach aimed at aligning climate strategies with the region’s socio-economic structures, structured around four strategic axes:

Strategy One: Revision and Development of Macro Agricultural Policies with an Integrated and Climate-Adaptation Approach

This includes two core policies:

Development of the policy-making and decision-making process,

Advancement of agricultural input management and production programs tailored toward adaptation and high efficiency.

Strategy Two: Technical, Economic, Social, and Cultural Empowerment Compatible with Climate change Effects

This includes two core policies:

Enhancement of economic, social, and cultural capacities,

Revision and development of education, technical, and research programs to improve farmers’ adaptive capacity.

Strategy Three: Adaptation-Driven Development in Crop and Horticultural Planning

This includes three core policies:

Climate-adaptive soil management,

Climate-adaptive agricultural water resources management,

Climate-driven organization of research and development in crop and horticulture sectors.

Strategy Four: Strengthening Sectoral Management Structures and Institutionalizing Cross-Sector Collaboration

This includes one core policy:

Creation and enhancement of legal and institutional capacities to align structures with climate change conditions.

This policy framework seeks to integrate institutional, technical, and social actions based on national and international frameworks to enhance the region's agricultural resilience.

In total, based on documentary analyses and expert opinions, 52 adaptation policies and implementation tools were developed for the agricultural sector in the Zayandeh-Rud Basin. To prioritize these policies, the PROMETHEE multi-criteria decision-making method was employed, providing a systematic, precise, and comparable evaluation of policy options.

Table 6 presents the PROMETHEE Flow Table generated by the Visual PROMETHEE software. According to Table 6, the top three priorities based on PROMETHEE flow values (ϕ) are:

Considering the ecological needs of the Gavkhouni Wetland and ensuring sustainable flow of the Zayandeh-Rud River (fair water distribution) with ϕ=0.901,

Basin-level water resource development planning with a holistic approach that enhances flexibility in meeting variable consumption needs (ϕ=0.722),

Amending laws and regulations related to land fragmentation (such as inheritance law) aimed at land consolidation, improving farmers' efficiency, and establishing a land bank (ϕ=0.594).

These policies ranked highest in the PROMETHEE Flow Table, highlighting their priority for enhancing agricultural resilience under climate change.

Table 6- Prioritization of climate change adaptation policies to enhance resilience using the PROMETHEE method

Rank	Code	Adaptation policies and tools	Phi	Phi+	Phi-
1	A_{19}	Considering the ecological needs of Gavkhouni Wetland and the sustainability of Zayandeh-Rud River flow (equitable water distribution)	0,9018	0,9418	0,0400
2	A_{21}	Basin-based water resources development planning with a holistic approach that provides flexibility in meeting variable consumption needs	0,7224	0,7351	0,0127
3	A_{1}	Reforming laws and regulations related to land fragmentation (such as inheritance law) to consolidate lands, increase farmers' efficiency, and establish a land bank	0,5947	0,6318	0,0371
4	A_{8}	Establishment of a groundwater level monitoring system and implementation of early warning systems	0,5947	0,6318	0,0371
5	A_{25}	Promoting and allocating facilities to encourage and facilitate income diversification among farmers (integrated agriculture, home-based businesses, etc.)	0,5947	0,6318	0,0371
6	A_{26}	Allocating technical and credit support to producer cooperatives and establishing weekly markets and direct sales stations for agricultural products	0,5947	0,6318	0,0371
7	A_{28}	Development of ancillary industries (processing and packaging of products), improvement of infrastructure, and economic diversification (home-based businesses, rural tourism, etc.)	0,5947	0,6318	0,0371
8	A_{31}	Establishment of regional support funds to protect farmers against price fluctuations of agricultural products or to provide facilities and credits	0,5947	0,6318	0,0371
9	A_{35}	Promoting the use of renewable energies	0,5947	0,6318	0,0371
10	A_{24}	Development of agricultural insurance adapted to climate change (such as weather index insurance) and farmers' retirement insurance	0,5147	0,5941	0,0794
11	A_{13}	Updating and completing the optimal water consumption pattern and water loss reduction program in the agricultural sector and implementing it	0,5024	0,6316	0,1292
12	A_{32}	Research and planning for the breeding of field and horticultural crops to produce varieties resistant to drought, aridity, and salinity	0,4457	0,5533	0,1076
13	A_{33}	Zoning of agricultural systems and production planning based on climatic capacity	0,4457	0,5533	0,1076
14	A_{23}	Development of farmer income stabilization funds against the effects of climate change	0,4124	0,5527	0,1404
15	A_{40}	Promoting heat- and drought-tolerant varieties and developing new adaptation inputs and technologies	0,3825	0,5410	0,1584
16	A_{27}	Providing educational and extension services to farmers to maintain and improve performance and optimal productivity	0,3359	0,5039	0,1680

17	A_{10}	Developing executive programs for water resource management by farmers and water user associations and establishing regional water markets	0,3324	0,5151	0,1827
18	A_{37}	Implementing infrastructure and training for the use of smart agriculture and precision agriculture	0,2947	0,4906	0,1959
19	A_{38}	Providing climate adaptation technologies	0,2947	0,4906	0,1959
20	A_{36}	Providing low-interest credits and facilities to farmers for purchasing technologies compatible with the basin’s climatic conditions	0,2335	0,4625	0,2290
21	A_{30}	Planning and preparing operational programs to expand alternative agricultural incomes with the aim of reducing pressure and reliance on basic resources (planning for farmers’ livelihood diversification)	0,1535	0,4249	0,2714
22	A_{42}	Planning for the cultivation of halophyte (salt-tolerant) or xerophyte field and horticultural crops in dry and saline areas and implementing in pilot regions	0,1457	0,4122	0,2665
23	A_{18}	Allocating low-interest technical and credit support for implementing modern and smart water systems and irrigation technologies (monitoring technologies such as sensors)	0,1175	0,4075	0,2900
24	A_{2}	Increasing farmers’ climate change-related information through enhanced in-person and virtual extension services	0,0825	0,3998	0,3173
25	A_{9}	Developing research and planning to improve agricultural irrigation efficiency according to hydrological unit capacity	0,0465	0,3824	0,3359
26	A_{17}	Allocating low-interest technical and credit support for expanding agriculture in controlled environments such as greenhouses, indoor, vertical, protected agriculture, etc.	0,0465	0,3824	0,3359
27	A_{34}	Allocating technical and credit support to farmers for the use of renewable energies	0,0433	0,3708	0,3275
28	A_{11}	Implementing small-scale water supply projects (water management measures and technologies)	0,0233	0,3573	0,3339
29	A_{3}	Establishment of an integrated spatial, descriptive, and market information system and creating an appropriate structure for sharing climate change-related information	-0,0665	0,3214	0,3878
30	A_{7}	Allocating subsidies to farmers for implementing on-farm water efficiency projects such as modern irrigation systems	-0,0665	0,3214	0,3878
31	A_{41}	Financial and technical support for producers of resilient and adapted crops in the basin	0,0665-	0,3214	0,3878
32	A_{43}	Policies related to best farming practices for field and horticultural production (priority for vulnerable areas)	0,0665-	0,3214	0,3878
33	A_{12}	Improvement of public irrigation canals, covering ditches, and reducing water losses in the agricultural sector	0,0904-	0,3220	0,4124
34	A_{16}	Developing, implementing, and operating programs for the reuse of return flows and treated wastewater in agriculture, considering ecological issues and piloting them	0,1294-	0,2963	0,4257
35	A_{29}	Compensation by the government for farmers’ losses due to climate change	0,1375-	0,3541	0,4916
36	A_{39}	Providing credits and facilities to innovative projects and agricultural knowledge-based companies in the field of climate change	0,1825-	0,2663	0,4488
37	A_{47}	Policies for best farming practices with emphasis on conservation agriculture	0,2412-	0,2502	0,4914
38	A_{46}	Developing biological and environmental management programs to address climate change (such as biodiversity programs, sustainable agriculture, greenhouse gas reduction, etc.)	0,3118-	0,2173	0,5290
39	A_{4}	Creating, designing, and integrating knowledge management for the dissemination of climate-smart agricultural technologies and methods	0,3573-	0,1951	0,5524
40	A_{6}	Regulations for the conservation and use of agricultural lands	0,4186-	0,1761	0,5947
41	A_{14}	Balancing and protecting surface and groundwater resources in view of climate change	0,4576-	0,1504	0,6080
42	A_{45}	Comprehensive soil fertility and plant nutrition program (monitoring the quality of agricultural lands and soil fertility)	0,4576-	0,1504	0,6080
43	A_{20}	Transparency and avoidance of arbitrary interpretation of laws and upstream documents regarding climate change management	0,5008-	0,1480	0,6488
44	A_{5}	Implementation of leading agricultural projects	0,5933-	0,1049	0,6982
45	A_{44}	Supplementary planning and implementation of conservation tillage programs according to climatic potential and biological capacity	0,5933-	0,1049	0,6982
46	A_{22}	Implementation of watershed management programs in the region	0,7427-	0,0553	0,7980

47	A_{15}	Volumetric water delivery to farmers, such as installation of smart meters on agricultural wells	0,8127-	0,0235	0,8363
48	A_{48}	Integration of responsible organizations and agencies or assigning climate change management to a relevant institution or organization in the agricultural sector	0,8127-	0,0235	0,8363
49	A_{49}	Revision of laws and regulations for the protection of surface and groundwater resources in light of climate change	0,8637-	0,0078	0,8716
50	A_{51}	Economic valuation of water (determining the economic value of water) and allocation management for agricultural uses	0,8637-	0,0078	0,8716
51	A_{52}	Limiting water abstraction through penalties for high-consumption actors	0,9037-	0,0008	0,9045
52	A_{50}	Familiarizing farmers with the principles of optimal product production (cropping pattern) considering land use planning and restrictions or prohibitions based on the basin's climatic conditions	0,9037-	0,0008	0,9045

Source: Research results

Following the prioritization of adaptation policies based on resilience criteria from the World Economic Forum with expert participation, the strategic analysis phase (SWOT) was carried out by intersecting internal factors (strengths and weaknesses), external factors (opportunities and threats), and 24 prioritized policies. This process led to the extraction of four major strategy types:

- Defensive Strategies: Focused on reducing threats by mitigating weaknesses.
- Conservative Strategies: Aimed at exploiting opportunities while addressing weaknesses.
- Aggressive Strategies: Targeted at leveraging strengths to capitalize on opportunities.
- Competitive Strategies: Designed to reduce threats by utilizing strengths.

Within this framework, each policy or implementation tool is explicitly linked to one or more of the four SWOT elements and purposefully designed to reduce vulnerability and enhance the resilience of the agricultural sector. The structure and outcomes of this intersection and strategic categorization are detailed in Table 7.

Table 7- SWOT matrix

External factors / **Internal factors**	**Opportunities** **O1، O2،O3،O4،O5، O6**	**Threats** **T1، T2،T3،T4،T5، T6**
Strengths S1، S2،S3،S3،S4، S5،S6	SO Strategies -A25(S1،S6،O2،O4،O6) -A26(S1،S6،O2،O4،O6) -A28(S1،S6،O2،O4،O6) -A31(S1،S6،O2،O4،O6) -A24(S5،S6، O4،O6) -A23(S1،S6،O2،O4،O6)	ST Strategies -A32(S2،S6،T2،T3،T4،T6) -A33(S2،S6،T1،T2،T3،T4،T6) -A27 (S4،S6،T2،T4) -A30(S4،S6،T2،T4،T6) -A42(S2،S6،T2،T4،T6) -A2(S4،S5،T1،T2،T3،T4،T5،T6)
Weaknesses W1، W2،W3،W4،W5، W6	WO Strategies -A35(W2،W3،W4،W5،O4،O6) -A40(W3،W4،W5،O1،O3) -A37(W3،W4،W5،O1،O3،O6) -A38(W3،W4،W5،O1،O3،O6) -A36(W3،W4،W5،O1،O3،O6) -A18(W3،W4،W5،O1،O3،O6)	WT Strategies -A19(W6،T1،T2،T3،T4،T6) -A21(W6،T1،T2،T3،T4،T6) -A1(W1،W6،T2،T4،T5) -A8(W6،T1،T2،T3،T4،T6) -A13(W6، T1،T2،T3،T4،T6) -A10(W6، T1،T2،T3،T4،T6)

Source: Research results

Stage Three: Formulation of Adaptation Policy Strategies to Enhance Resilience to Climate change in the Zayandeh-Rud Basin

The objective of this stage is to develop adaptation policy strategies that are sustainable and feasible in the face of climate change, with flexibility to allow strategy substitution in unforeseen circumstances.

This stage incorporates participatory governance, engaging farmers and agricultural exporters (private sector actors) as key agents to overcome climate change challenges. Accordingly, using a political Delphi method, a homogeneous sample of 20 agricultural producers and exporters—knowledgeable and actively involved in the basin's agricultural issues—was selected with the assistance of the Isfahan Provincial Agricultural Jihad.

Considering the basin's strategic position and the results of the Quantitative Strategic Planning Matrix (QSPM), the defensive, competitive, conservative, and aggressive strategies were ranked by attractiveness. Due to the basin's defensive strategic position, the defensive strategy was the primary focus.

For the defensive strategy, the highest attractiveness was assigned to addressing the ecological needs of the Gavkhouni Wetland and maintaining sustainable flow of the Zayandeh-Rud River (fair water distribution) (A19) with a score of 1.462. The second priority was basin-level water resource development planning with a holistic approach providing flexibility to meet variable demands (A21), scoring 1.383. The third-ranked priority was updating and completing the optimized water consumption pattern and implementing water loss reduction programs in agriculture (A13) with a score of 1.359.

The Quantitative Strategic Planning Matrix for the defensive strategy is presented in Table 8.

Table 8- Quantitative strategic planning matrix (QSPM) for defensive strategy

Factors	Weight	Strategy (WT)											
		A_{19}		A_{21}		A_1		A_8		A_{13}		A_{10}	
Threats (T)		AS	TAS	AS	TAS	AS	TAS	AS	TAS	AS	TAS	AS	TAS
T_1	0.0443	4	0.177	4	0.177	2	0.089	4	0.177	3	0.133	3	0.133
T_2	0.0435	4	0.174	4	0.174	3	0.131	4	0.174	4	0.174	3	0.131
T_3	0.042	4	0.168	4	0.168	2	0.084	3	0.126	4	0.168	4	0.168
T_4	0.0413	4	0.165	4	0.165	2	0.083	4	0.165	4	0.165	4	0.165
T_5	0.0404	4	0.162	4	0.162	4	0.162	3	0.121	3	0.121	3	0.121
T_6	0.0402	4	0.161	4	0.161	3	0.121	3	0.121	3	0.121	3	0.121
Weaknesses(W)													
W_1	0.0304	3	0.091	3	0.091	4	0.122	2	0.061	2	0.061	2	0.061
W_2	0.0287	3	0.086	2	0.057	3	0.086	2	0.057	2	0.057	2	0.057
W_3	0.0279	3	0.084	2	0.056	3	0.084	2	0.056	3	0.084	2	0.056
W_4	0.0278	2	0.056	2	0.056	3	0.083	2	0.056	4	0.111	2	0.056
W_5	0.0238	2	0.048	2	0.048	3	0.071	2	0.048	4	0.095	2	0.048
W_6	0.0228	4	0.091	3	0.068	3	0.068	3	0.068	3	0.068	2	0.046
TOTALS TAS			1.462		1.383		1.183		1.23		1.359		1.161
Priorities			1		2		5		4		3		6

Source: Research results

The QSPM results confirmed the PROMETHEE ranking; in other words, the adaptation policies prioritized by experts were validated by farmers and agricultural exporters and corresponded respectively to the defensive, competitive, conservative, and aggressive strategies. The defensive strategies emphasized fair water distribution, development-oriented water resource planning, optimization of consumption and reduction of water losses, groundwater level control, reform of laws related to land fragmentation, and farmer participation in water resource management. This matrix demonstrated the relative attractiveness of each policy, providing a solid basis for decision-making.

Based on the research findings, a comprehensive set of policies and implementation actions was developed to enhance agricultural resilience in the Zayandeh-Rud Basin. The operational program for these strategies is presented in Table 9, which can serve as a practical roadmap for policymakers and agricultural sector managers.

Table 9- Action plan for policy strategies consistent with increasing agricultural resilience in the Zayandeh-Rud Basin

Strategy type	Selected policies (Code)	Time priority	Targeted resilience capacity	Operational actions	Required resources	Evaluation indicators
Defensive (Survival)	A19, A21, A13, A8, A1, A10	Short-term	(Absorptive)	-Developing and implementing water distribution regulations -Establishing monitoring and warning systems -Training farmers -Implementing land consolidation projects -Establishing regional water markets -Reforming inheritance laws	Government budget, water and legal experts, monitoring systems, local organizations	Percentage of equitable water distribution, reduction in water conflicts, number of consolidated lands, reduction in water losses
Competitive	A33, A32, A42, A27, A30, A2	Mid-term	(Adaptive)	-Developing zoning and production plans based on climate -Implementing breeding projects -Piloting cultivation of resilient crops -Organizing training and extension courses -Supporting alternative livelihoods	Research budget, research centers, extension experts, educational resources	Number of resilient crops produced, number of trained farmers, increase in alternative incomes, increased climate awareness
Conservative	A18, A37, A40, A36, A35, A38	Long-term	(Transformative)	Providing low-interest loans and facilities -Installing smart water systems -Training in precision agriculture -Promoting renewable energy in farms -Delivering innovative technologies to farmers	Bank credits, technology equipment, specialized training, government incentives	Number of smart systems installed, increased use of renewable energy, increased water and energy efficiency
Aggressive	A25, A28, A26, A31, A34, A23	Long-term	(Transformative)	-Providing facilities for home-based and integrated farming jobs -Establishing and equipping processing and packaging industries -Launching agricultural markets -Establishing regional support funds -Supporting renewable energy adoption	Government and bank credits, industrial infrastructure, cooperatives and NGO support	Number of alternative jobs created, increase in value-added products, number of active support funds, increased farmers' income

Source: Research results

The results of this study demonstrated that defensive strategies, particularly those related to integrated water resources management, reform of land fragmentation laws, and technological advancement, hold the highest priority for enhancing agricultural resilience in the Zayandeh-Rud Basin. These findings align with previous studies (Safavi *et al*., 2015; Sadeghi *et al*., 2019) that emphasize the importance of water governance and institutional structure reform. However, this study advances by employing multi-criteria decision-making approaches and integrating international frameworks, thus offering more localized adaptation policies.

From a practical perspective, the implementation of prioritized policies requires strengthening stakeholder participation, investing in modern technologies, and reforming governance processes. Research limitations include the lack of field data in some regions and difficulties in engaging all stakeholders. It is recommended that future studies incorporate scenario-based approaches and long-term policy impact assessments.

Considering the unique climatic, environmental, and social conditions of each watershed in the country, it is essential that the results and proposed strategies be independently tailored and localized based on each area's specific characteristics. Nevertheless, because this study is grounded in recognized international frameworks such as the Sendai Framework for Disaster Risk Reduction and the World Economic Forum's resilience criteria, and utilizes standard analytical tools (SWOT, IFE, EFE, AHP, PROMETHEE, and QSPM), along with the fact that many of the key challenges—including water scarcity, infrastructural weakness, and governance issues—are common across other watersheds, the proposed model and identified adaptation policies have relative generalizability and applicability to other regions. Therefore, the findings can serve as a reference framework for designing and developing agricultural resilience policies in other watersheds in the country, provided that local adaptation processes and active stakeholder participation are taken into account.

Conclusion and Recommendations

The findings of this study highlight the fundamental challenges and opportunities for agricultural resilience in the Zayandeh-Rud Basin under the pressures of climate change. The defensive position of the agricultural sector in the IE matrix indicates significant vulnerability, primarily due to water transfer and scarcity, land fragmentation and subsidence, and weaknesses in infrastructure and modern technologies. These challenges align with prior studies in arid and semi-arid regions, where climate change exacerbates resource limitations (Safavi *et al*., 2015; Teymouri *et al*., 2023).

Integrated and basin-scale water resources management was identified as the most critical resilience criterion, consistent with global research emphasizing the key role of water management in agricultural adaptation (Talashi & Kafash, 2019; Srivastav *et al.*, 2021). The high priority for modern technology development underscores the necessity of investing in efficient technologies like monitoring systems and sensors to reduce water waste and increase water use efficiency.

Reforming laws and regulations related to land fragmentation, including inheritance laws, for land consolidation and enhanced farmer efficiency ranked as the second most important factor. This corresponds with previous research indicating land fragmentation as a major barrier to agricultural productivity and sustainable rural development (Golmohammadi, 2021; Hadi Pour *et al*., 2019). Furthermore, designing and implementing water resource management programs by farmers and water user associations, alongside establishing regional water markets, ranked third in importance. These play a pivotal role in local participation and improving water governance, aligning with previous findings that stress strengthening local capacities and participatory mechanisms for optimal water resource management (Islamy & Rahimi, 2019; Taleshi, 2018).

The integration of various tools in a comprehensive strategic management model—including IFE, EFE, IE, SWOT, AHP, PROMETHEE, and QSPM—provided a clear and robust framework for evaluating complex adaptation options, combining quantitative and qualitative data simultaneously. This participatory approach notably enhances analytical precision, legitimacy, and applicability of findings for policymakers and implementers.

Overall, the study's results indicate that to enhance agricultural resilience in the Zayandeh-Rud Basin, policies and strategies must be designed and implemented comprehensively, collaboratively, and based on optimal water resource management and modern technologies. Legal structure reforms and strengthening local capacities are also key factors for success.

Policy and Operational Recommendations

A. National and Provincial Policy-Level Recommendations

Based on the study's findings pointing to the defensive status of agriculture in the Zayandeh-Rud Basin and key challenges such as water scarcity, land fragmentation, weak infrastructure, and the need for integrated governance, it is recommended to:

- Develop a climate adaptation strategic document for the Zayandeh-Rud Basin with collaboration from the Ministry of Agriculture Jihad, Environmental Protection Organization, and Ministry of Energy.
- Integrate adaptation policies into Isfahan province's budgetary programs, particularly in agriculture, natural resources, and water.
- Establish a Climate and Agricultural Resilience Integrated Management Task Force, comprising government, private sector, and regional agricultural association representatives.

B. Operational and Local-Level Recommendations

Aligned with priority policies emphasizing water use efficiency, livelihood diversification, and technology development, it is suggested to:

- Revise cropping patterns emphasizing drought and temperature-resistant crops such as medicinal plants and dryland farming.
- Enhance livelihood diversification for farmers by supporting supplementary occupations (e.g., rural tourism, handicrafts, fisheries, and semi-industrial livestock).
- Develop climate monitoring and early warning systems via mobile applications and field training for farmers.
- Promote climate-indexed agricultural insurance supported by the government to reduce farmers' financial risks.

Additionally, considering the study's findings and focusing on the defensive (WT) strategy to reduce threats and overcome weaknesses for agricultural survival against climate change, the following steps are proposed:

- Step 1: Current Situation Analysis and Regional Action Planning

Identify priority crisis areas in upstream, midstream, and downstream parts of the basin.

Create an integrated database on farmers, water resources, cropping patterns, and climatic indices.

Monitor climatic changes and analyze long-term trends in temperature, precipitation, and water resources. Responsible bodies: Isfahan Governorate, Agricultural Jihad, Meteorological Organization.

- Step 2: Water Demand Management and Agricultural Water Use Efficiency

Assign precise volumetric water quotas for each farm and record in smart systems.

Install smart meters on authorized wells for real-time monitoring.

Promote low-water crops such as saffron, medicinal plants, and dryland wheat.

Responsible bodies: Regional Water Company, Agricultural Jihad, Agricultural Guilds.

- Step 3: Enhance Economic Resilience and Reduce Income Dependency on a Single Source

Provide low-interest loans to develop complementary occupations (dryland orchards, light livestock, solar greenhouses).

Establish multifunctional local cooperatives for marketing and selling diverse products.

Train young farmers in business skills.

Responsible bodies: Agricultural Jihad, Cooperatives Office, Agricultural Bank.

- Step 4: Institutionalize Climate Index Insurance and Risk Management

Design agricultural insurance based on climatic indices.

Create climate damage funds with government support and private sector participation.

Promote insurance culture through education and financial incentives.

Responsible bodies: Central Insurance, Agricultural Products Insurance Fund.

- Step 5: Local Empowerment and Education

Conduct workshops on smart farming, climate change, and resilience.

Utilize lead farmers' experience to transfer knowledge.

Set up local "Agricultural Resilience Centers" for consultation and promotion.

Responsible bodies: Agricultural and Natural Resources Research Center, Vocational Training Centers, Universities.

- Step 6: Institutionalize Participatory Water and Agricultural Governance

Establish Basin Climate and Agricultural Management Council with farmer representatives.

Enhance transparency in water allocation and provide online complaint systems.

Draft a legal charter for water and farmers' rights in Zayandeh-Rud.

Responsible bodies: Ministry of Energy, Islamic Parliament, Governorate.

Expected Outputs

- Preservation of employment levels and sustainable livelihoods for farmers.
- Reduction of social conflicts stemming from water issues.
- Increased efficiency and reduced dependency on groundwater.
- Enhanced social and economic resilience of the region against climate change.

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جلد ۳۹، شماره ٤، زمستان ١٤٠٤، ص. ٤١٧-٣۹۷

تدوین راهبرد سیاست‌های سازگار با افزایش تاب‌آوری ناشی از تغییر اقلیم (مطالعه موردی: کشاورزی حوضه زاینده‌رود)

اسماعیل حیدری رامشه[1]- آرش دوراندیش[1*]- سیدصفدر حسینی[1]- سعید یزدانی[1]

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چکیده

تغییرات اقلیمی با تأثیرگذاری تدریجی و پیچیده، خسارات فزاینده‌ای را به بخش کشاورزی مناطق خشک و نیمه‌خشک ایران از جمله حوضه زاینده‌رود تحمیل کرده است. این پژوهش با هدف تدوین راهبرد سیاست‌های سازگاری به‌منظور افزایش تاب‌آوری کشاورزی در مواجهه با تغییر اقلیم این حوضه، بر اساس سند چارچوب کاهش ریسک بلایا (SFDRR)، و معیارهای تاب‌آوری مجمع جهانی اقتصاد (۲۰۱۳) انجام شد. روش تحقیق توصیفی-تحلیلی و مبتنی بر ترکیب مطالعات اسنادی، پیمایش میدانی و روش دلفی سیاستی برای اخذ اجماع خبرگان و جمع‌آوری داده‌ها انجام گرفت. نمونه‌گیری به‌صورت هدفمند و از میان اساتید دانشگاهی، کارشناسان جهاد کشاورزی و تولیدکنندگان و صادرکنندگان محصولات کشاورزی که شناخت مناسبی از مباحث تغییر اقلیم، سیاست‌های سازگاری و تاب‌آوری داشتند، صورت پذیرفت. ابزار گردآوری داده‌ها شامل چهار پرسشنامه ساختاریافته (برای شناسایی نقاط قوت و ضعف، وزن‌دهی معیارهای تاب‌آوری، اولویت‌بندی سیاست‌ها و انتخاب راهبردها) و مصاحبه‌های نیمه‌ساختاریافته بود. در گام نخست، برای تعیین موقعیت راهبردی کشاورزی حوضه زاینده‌رود، از ماتریس‌های ارزیابی عوامل داخلی (IFE)، عوامل خارجی (EFE) و ماتریس موقعیت داخلی-خارجی (IE) استفاده شد. سپس به‌منظور اولویت‌بندی سیاست‌های سازگار با افزایش تاب‌آوری ناشی از تغییر اقلیم، از فرآیند تحلیل سلسله‌مراتبی (AHP) و روش تصمیم‌گیری چندمعیاره PROMETHEE بهره گرفته شد. راهبردهای مناسب نیز با استفاده از تحلیل SWOT توسعه و استخراج گردید و در نهایت، با به‌کارگیری ماتریس برنامه‌ریزی راهبردی کمّی (QSPM)، جذابیت نسبی و قابلیت اجرای هر راهبرد ارزیابی و سیاست‌های نهایی قابل‌اجرا انتخاب شد. یافته‌ها نشان داد که کشاورزی حوضه زاینده‌رود با امتیاز نهایی عوامل داخلی ۲.۰۴ و عوامل خارجی ۲.۱۲ در وضعیت تدافعی (بقا) قرار دارد و تاب‌آوری آن به‌دلیل انتقال و کمبود آب، خردشدگی و فرونشست اراضی و ضعف زیرساخت‌های نوین، پایین است. جذاب‌ترین سیاست‌های سازگاری شناسایی‌شده در راهبرد تدافعی، شامل توزیع عادلانه آب (TAS=1.46)، برنامه‌ریزی توسعه‌محور منابع آب (TAS=1.38)، بهینه‌سازی مصرف و کاهش تلفات آب (TAS=1.35)، کنترل سطح آب‌های زیرزمینی (TAS=1.23)، اصلاح قوانین مرتبط با خردشدگی اراضی (TAS=1.18) و مشارکت کشاورزان در مدیریت منابع آب (TAS=1.16) می‌باشد. راهکارهای پیشنهادی این پژوهش عبارت‌اند از: تقویت حکمرانی یکپارچه و حوضه‌محور منابع آب، اجرای مدل مدیریت راهبردی مشارکتی، سرمایه‌گذاری در فناوری‌های نوین و نرم، بازنگری تدریجی در قوانین و مقررات آب و گسترش تحقیقات و تدوین راهبرد ملی. نتایج این پژوهش، راهکارهای عملی و مبتنی بر مشارکت ذی‌نفعان را برای سیاست‌گذاران جهت ارتقای پایداری و تاب‌آوری کشاورزی در مناطق آسیب‌پذیر را پیشنهاد می‌نماید.

واژه‌های کلیدی: برنامه‌ریزی راهبردی، حکمرانی مشارکتی، راهبردهای تاب‌آوری کشاورزی، سیاست‌گذاری سازگار

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