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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?

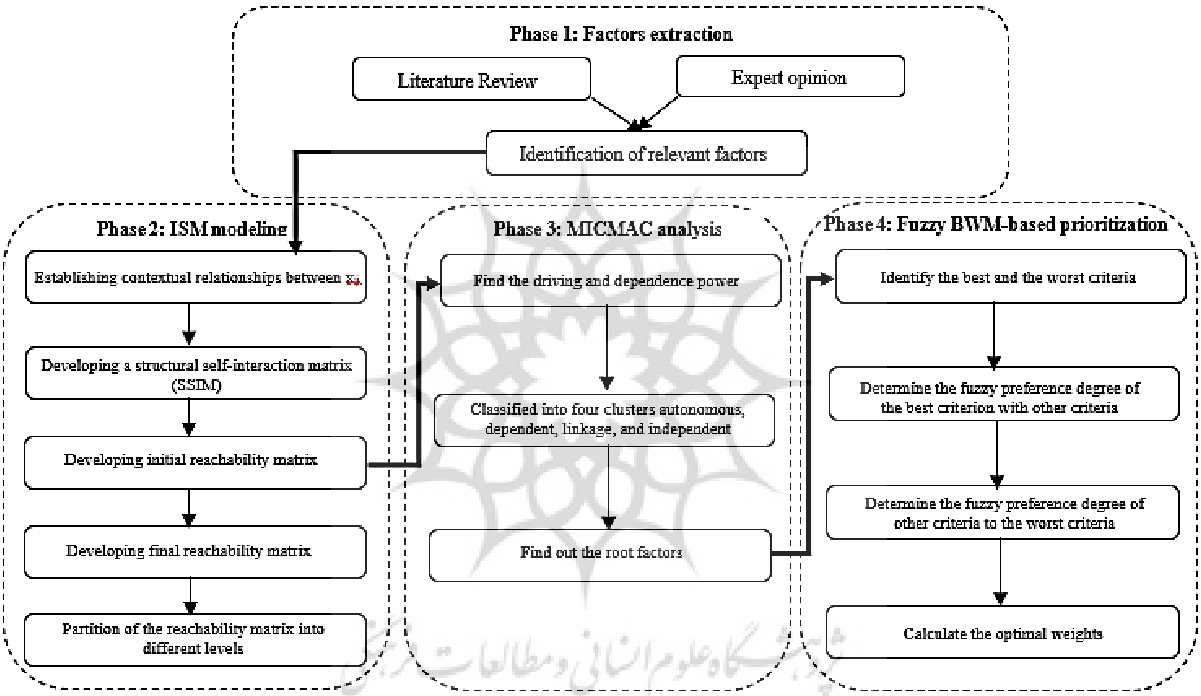

Figure 1- Framework of the approach

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 ($K \geq 1$), 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, $1 \times 1 = 1$ 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).

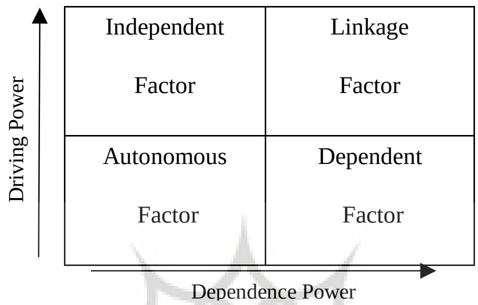

Figure 2- MICMAC diagram (Driving Power-Dependence Power)

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.

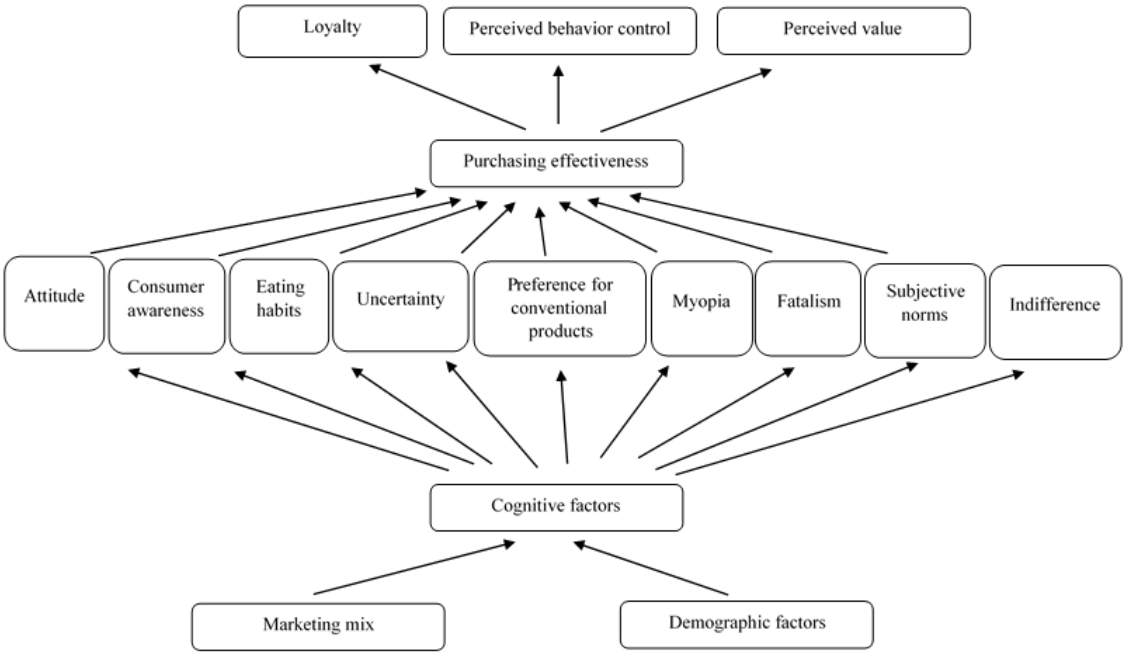

Figure 3- ISM modeling

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.

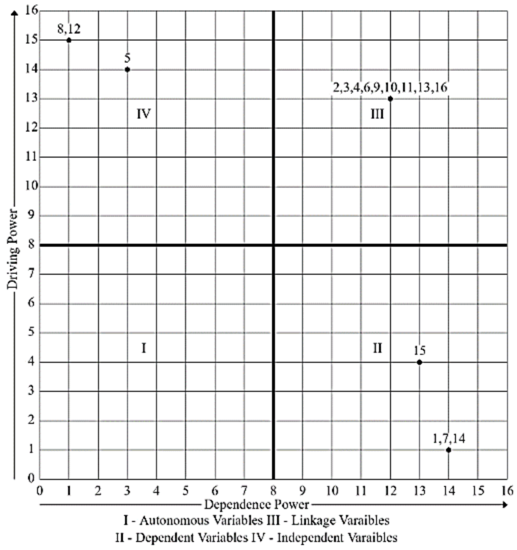

Figure 4- Driving power and dependence diagram

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:

$$\tilde{p} = \frac{1}{n}\sum_{i=1}^{n} \lambda_i \, \tilde{p}_i \qquad (5)$$

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:

$$\lambda_i = \frac{H_i}{\sum_{k=1}^{n} H_k} \qquad (6)$$

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 آنتی بیوتیک: 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.

واژه‌های کلیدی: آمیخته بازاریابی، بدون آنتی‌بیوتیک، طیور

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