

Article

Analysis of Purchase Intention for Biopreservative-Treated Chicken and Consumer Segmentation Using Unsupervised Machine Learning

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Abstract

Biopreservatives are emerging as a promising alternative to conventional food preservation methods. However, there is limited empirical evidence integrating validated psychometric instruments with advanced unsupervised segmentation techniques to identify heterogeneous consumer profiles regarding biopreserved chicken consumption. To address these limitations, self-organizing maps (SOMs) have been widely used as unsupervised learning tools that reduce dimensionality, preserve topological relationships, and facilitate the visualization of latent structures in multivariate datasets. This study aims to analyze the factors influencing the acceptance of biopreservation in chicken consumption through a strategic segmentation based on unsupervised machine learning and behavioral dimensions. This methodological design enables the capture of behavioral heterogeneity, the identification of strategic consumption profiles, and the generation of empirical evidence to support future research and communication strategies related to biopreservation technologies in similar consumer contexts. In this study, 323 instances were topologically organized into 16 clusters, grouping individuals with similar behavioral patterns. The descriptive analysis of clusters revealed highly differentiated consumer profiles in terms of Consumer acceptance, cold chain practices, and Knowledge of food microorganisms. The high-acceptance exploratory segment achieved the maximum score (5.00) in knowledge of beneficial microorganisms (V14), acceptance of their use in chicken preservation (V15), and familiarity with lactic acid bacteria (V16). The three-dimensional structure identified through Exploratory Factor Analysis (EFA) not only provided statistical validation of the instrument but also established a conceptual framework for interpreting the SOM's topology. From a practical perspective, the findings highlight the relevance of consumer heterogeneity and suggest that consumer knowledge may play an important role in the acceptance of biopreservation technologies. These findings provide useful insights for future studies aimed at understanding the factors that influence consumer acceptance of biopreservation technologies.

Keywords: poultry; biopreservation; chicken; lactic acid bacteria; consumer acceptance; purchase experience; psychometric validation; unsupervised learning



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1. Introduction

Poultry production has consolidated its position as one of the fastest-growing sectors worldwide, as chicken constitutes a major source of animal protein and accounts for 36.7% of total global meat production. In 2023, global output reached a record 103.8 million metric tons [1,2]. The United States, Brazil, and China are projected to maintain their leadership in production, with significant contributions from other countries, while México ranks sixth globally [3,4].

In this high-production context, operational efficiency within the poultry industry is critical to ensuring food security and economic sustainability. However, inadequate practices such as cold chain failures, the use of equipment and transportation under suboptimal hygienic conditions, and improper packaging may lead to serious consequences, including economic losses and substantial food waste resulting from food safety breaches [5]. Globally, a significant proportion of food is lost during production, processing, storage, and distribution, underscoring the need to reduce losses across the food supply chain to guarantee food security in both quantitative and qualitative terms [6,7]. Consequently, food spoilage has contributed to food insecurity in various regions worldwide [8].

This challenge is exacerbated by the inherently perishable nature of meat. Perishable foods are highly susceptible to spoilage due to microbial proliferation and, in the case of meat, lipid oxidation and autolytic enzymatic activity. These processes cause discoloration, the development of off-odors and off-flavors, and undesirable alterations in organoleptic properties such as color, texture, appearance, and taste resulting from metabolites that compromise suitability for human consumption [9–13]. Chicken meat, due to its high perishability, is particularly vulnerable to microbiological spoilage, leading to quality deterioration and financial losses [7,14].

Among spoilage microorganisms, species of the genus *Pseudomonas* are especially noteworthy. These ubiquitous Gram-negative rods predominate in aerobically packaged meat and are widely associated with spoilage and economic losses in the food industry. Certain strains are capable of growth in a temperature range of 4 to 5 °C [7,15]. Their presence significantly degrades food quality, leading to consumer rejection and potential damage to brand reputation [15]. Similarly, members of the Enterobacteriaceae family may constitute a substantial proportion of the spoilage microflora in refrigerated chicken meat [16,17] and morphological and physiological traits. It is relevant in food systems due to its role in spoilage, its potential as a group of foodborne pathogens, and its utility as an indicator of fecal contamination. It includes genera such as *Escherichia*, *Salmonella*, and *Shigella*, which are associated with intestinal infections [18,19]. Therefore, controlling foodborne pathogens in meat and meat products is a major challenge for the industry and may be addressed through the strategic application of biocompounds or biopreservatives [20].

Climate change and rising ambient temperatures have further intensified the need to develop technologies that extend chicken shelf life without compromising safety [14]. Consequently, designing effective waste management and reduction strategies is essential for mitigating these impacts and strengthening the sustainability of the poultry supply chain [21].

In response to these challenges, food technology has evolved toward the development of non-thermal preservation methods aimed at extending freshness without compromising nutritional value or sensory properties. These technologies include ultrasound, high-pressure processing (HPP), ultraviolet (UV) radiation, pulsed electric fields (PEF), cold plasma (CP), irradiation, and electrolyzed water [22]. Such approaches enable microbial inactivation and shelf-life extension without the application of heat, thereby minimizing quality deterioration.

However, their industrial implementation remains challenging due to the high costs associated with equipment acquisition and maintenance, elevated energy requirements,

and scalability limitations compared with laboratory-scale applications. Major barriers to industrial adaptation include continuous-flow processing, ensuring homogeneous treatment in large volumes, compatibility with packaging systems, and regulatory constraints. Consequently, many small and medium-sized enterprises continue to rely on conventional preservation methods such as refrigeration [23–26].

In parallel, biopreservation has emerged as a promising alternative. This approach employs beneficial microorganisms or their metabolites to enhance food safety and extend product shelf life [20]. In particular, lactic acid bacteria (LAB), which are part of the natural microbiota of fermented foods and the human gastrointestinal tract [27], have gained attention as a natural and efficient alternative to conventional preservation methods because they inhibit pathogenic microorganisms without adversely affecting the sensory properties of the product. Unlike many non-thermal technologies that exert their effect only at the time of treatment, LAB can continue to grow and suppress spoilage microbiota during storage [28–30].

Among the reported applications of biopreservation is the preservation of fresh meat, where protective cultures have demonstrated the ability to inhibit *Listeria monocytogenes*, *Enterobacteriaceae*, *Pseudomonas*, and *Brochothrix thermosphacta* [31,32]. Likewise, metabolites and postbiotics derived from lactic acid bacteria (LAB) have shown positive effects on raw chicken quality by delaying sensory deterioration, improving odor and overall acceptability, and reducing the growth of spoilage microorganisms during refrigerated storage [33–35].

Additionally, these compounds contribute to the instrumental and physicochemical stability of meat by promoting increased lightness (L^*) and the preservation of reddish color tones (a^*), as well as improving textural properties such as water-holding capacity and meat tenderness [36,37]. From a physicochemical perspective, reductions in lipid oxidation and enhanced protein stability during storage have also been reported [36,37].

Despite these advances, the widespread implementation of biopreservation faces several constraints, including a lack of process standardization that limits large-scale adoption. Furthermore, regulatory frameworks governing the use of microorganisms and antimicrobial compounds vary across countries, hindering the international commercialization of biopreserved products [38].

The efficacy of biopreservatives may also depend on storage time and temperature, product pH, and interactions with other food components or members of the food microbiota, highlighting the need for continued research to optimize their application [20].

In this context, technical and regulatory barriers are not the only challenges to adoption; commercial viability also depends on consumer acceptance. Perceptions of naturalness, safety, and sustainability directly influence purchase intention [39]. Nevertheless, empirical evidence integrating validated psychometric instruments with advanced unsupervised segmentation techniques to identify heterogeneous consumer profiles regarding biopreservatives in chicken meat remains limited.

Traditionally, consumer segmentation has relied on partition-based clustering techniques such as K-means. However, determining the optimal number of clusters and assessing sensitivity to outliers are recognized methodological limitations [40]. To address these limitations, Self-Organizing Maps (SOMs) have been widely used as unsupervised learning tools that reduce dimensionality while preserving topological relationships and facilitating the visualization of latent structures in multivariate datasets [41].

The stochastic SOM projects high-dimensional data onto a two-dimensional grid, enabling the identification of similarity regions without imposing distributional assumptions and maintaining topological coherence among similar observations [41]. This property is

particularly relevant in behavioral studies, where relationships among variables may be nonlinear and multidimensional.

Moreover, integrating SOM with K-means in a two-stage approach has been shown to improve the stability and quality of the resulting segments by combining SOM's exploratory capacity with K-means' partition consolidation [40]. From a methodological standpoint, stochastic implementations of SOM—such as those developed in the R environment via the SOMbrero package (v. 1.5.0)—enable the use of variants tailored to different data structures, including numerical matrices and relational datasets [42], thereby enhancing the robustness of unsupervised analyses.

The SOM's algorithm works in four phases: (1) initialization, (2) competition, (3) cooperation, and (4) adaptation [43].

In the first stage, each node is assigned a random weight vector. At this stage, the map has no defined order and there are no visible relationships between the nodes and the data.

In the second stage, a random data point x is selected from the dataset. Then, the distance (usually the Euclidean distance) between x and the weight vector w of each node is calculated. The node with the smallest distance is designated as the Best Match Unit (BMU).

$$BMU = \operatorname{argmin}_i ||x - w_i||$$

In the third stage, the environment around the BMU is defined. Nodes physically close to the BMU in the network are strongly influenced by it. Similarly, nodes farther away are less influenced. The environment's radius decreases over time, meaning that at the beginning of training, the map undergoes large global changes, and subsequently, local details are refined. Finally, in the fourth stage, the adaptation stage, the weights are updated. Here, the weights of the BMU and its neighbors are updated to more closely resemble the input vector x . This brings the grid closer to the data points.

$$w_i(t+1) = w_i(t) + \Theta(i, t)\alpha(t)[x(t) - w_i(t)]$$

where $\alpha(t)$ is the learning rate, which decreases over time, and $\Theta(i, t)$ is the neighborhood function.

In this way, self-organizing maps (SOMs) keep similar data points close together. If two points are neighbors in a high-dimensional space, they are likely to be neighbors on the map as well. They are excellent for finding hidden patterns in unlabeled data, which are often visualized as matrices [41].

In this framework, the present study aims to analyze the determinants of acceptance of biopreservatives in chicken consumption through a strategic segmentation based on unsupervised machine learning and behavioral dimensions. This methodological design enables the capture of behavioral heterogeneity, the identification of strategic consumption profiles, and the generation of empirical evidence to support future research and commercial implementation strategies in comparable consumer populations.

2. Materials and Methods

2.1. Dataset Description

This study was conducted in Aguascalientes, México, using a cross-sectional survey administered through Microsoft Windows Forms and distributed via WhatsApp using convenience sampling. Participants from different socioeconomic backgrounds and age groups voluntarily responded after providing informed consent. The target population consisted of adult chicken consumers residing in Aguascalientes, México. Inclusion criteria required participants to be at least 18 years of age and to report consuming chicken meat. Responses were excluded if questionnaires were incomplete or contained missing values in

the variables included in the multivariate analyses. Data collection was conducted between July 2025 and December 2025. A total of 445 responses were received. After data cleaning and listwise deletion of incomplete responses, 323 valid questionnaires were retained for analysis.

The analyzed dataset initially comprised 33 variables. After data cleaning and listwise deletion of cases with missing values (0.1% in predictor variables and 0.03% in the target variable), a final sample of 323 valid instances and 16 quantitative variables was obtained for multivariate analysis and machine learning training. The adequacy of the sample size was supported by the subject-to-item ratio (N:p), one of the most widely accepted criteria in psychometrics and sensory analysis. Methodological literature recommends a minimum ratio of 5:1 and ideally 10:1 for factor analysis and dimensionality reduction techniques [44]. With 323 observations and 33 variables, the present study achieved a ratio of 9.78:1, indicating a robust sample structure and ensuring the stability and reproducibility of the extracted factors. Furthermore, according to the classification proposed by Comrey and Lee, sample sizes above 300 are considered “good” for multivariate analysis.

The final sample included 236 women, 85 men, and 2 participants who preferred not to specify their sex. Participants ranged from 18 to 65 years old, with most respondents between 31 and 50 years of age (53.5%). The sample was characterized by a high educational level, predominantly consisting of participants with higher education (40.2%) and postgraduate studies (39.0%). Additionally, more than 80% of respondents reported habitual chicken consumption, mainly between one and four times per week.

2.2. Instrument Design and Validation

The data collection instrument was designed as a structured survey aimed at evaluating critical dimensions of consumer behavior. Its development was based on the Conceptual Design Guide of INEGI and the criteria established in the Mexican Standard.

The questionnaire included five-point Likert-scale items (1–5) to assess purchasing habits, household handling practices, consumer knowledge, and acceptance. All variables included in the Exploratory Factor Analysis (EFA) were treated as continuous variables, following common practices in psychometric research for Likert-type scales.

As part of the validation process, content validity was first established through expert judgment, followed by an Exploratory Factor Analysis (EFA) to assess the underlying dimensional structure and construct validity of the instrument. Factor extraction was performed using Principal Axis Factoring, given its suitability for identifying latent constructs. An oblique rotation method (Promax with Kaiser normalization) was applied, allowing correlations among factors, which is appropriate in consumer behavior studies where latent dimensions are expected to be interrelated.

The number of factors retained was determined based on three criteria: eigenvalues greater than 1, inspection of the scree plot, and theoretical interpretability of the factor solution. Items were retained based on factor loadings of at least 0.40, acceptable communalities, absence of problematic cross-loadings, and theoretical interpretability. Variables that failed to meet these criteria were removed through an iterative refinement process until a stable and interpretable factor structure was obtained.

Sampling adequacy was confirmed using the Kaiser–Meyer–Olkin (KMO) measure (0.729) and Bartlett’s test of sphericity ($\chi^2 = 581.727$, $p < 0.001$), indicating that the data were suitable for factor analysis.

2.3. Strategic Segmentation Using Machine Learning (SOM)

The central methodological contribution of this study lies in applying machine learning techniques to identify strategic consumer segments, thereby overcoming the limitations of

traditional descriptive statistical approaches. A Self-Organizing Map (SOM) model was implemented, which is a type of artificial neural network trained through unsupervised learning to generate a discretized two-dimensional representation of the data.

To avoid methodological circularity, purchase intention (V17) was excluded from the Self-Organizing Map (SOM) training phase. The neural network was trained as an unsupervised model using only the 15 behavioral and knowledge variables (V1 to V16). V17 was used exclusively as an external, passive variable projected onto the consolidated clusters after training to assess how the different behavioral profiles intrinsically correlated with product acceptance. During this phase, the algorithm has no indication of whether an individual has a high or low purchase intention. Individuals are grouped into the 16 clusters based purely on the homogeneity of their behavioral profiles.

Once the network architecture has stabilized and the meta-cluster has consolidated the boundaries of the 16 segments, each of the 323 instances (consumers) receives a definitive label indicating which group it belongs to. Up to this point, the clusters are strictly behavioral. With the groups now closed and immutable, the original database is revisited, and the column for variable V17 is reintroduced. Since each consumer is already assigned to a cluster, variable V17 is automatically segmented into 16 independent subsets of data. This procedure avoids confirmation bias (circularity). By passively training the SOM with V17, the acceptance level is achieved because the knowledge and habits profile of this group organically predicts high technological acceptance.

To assess the statistical robustness of the identified segments, a post-hoc descriptive analysis of the resulting clusters was performed. For each group discussed, the number of individuals (n), mean ($\bar{x}$), standard deviation (SD), and 95% confidence intervals were reported.

Additionally, to ensure a comprehensive evaluation of the model, not only was the Quantization Error (QE) reported, but the Topographic Error (TE) was also calculated to measure the preservation of neighborhood relationships in the input space on the two-dimensional grid.

To ensure the stability of the results and eliminate the variability inherent in random initializations, an initialization based on Principal Component Analysis (PCA) was employed. This procedure aligns the initial weight vectors with the axes of greatest variance in the data, guaranteeing reproducible convergence and global topological ordering from the start of training.

The analysis followed a two-stage methodological design: first, the use of Self Organized Maps (SOM) for dimensionality reduction and topographic organization of the 323 instances, and second, hierarchical meta-clustering (using Ward's criterion) on the prototype vectors of the 100 nodes. This hybrid approach combines the exploratory capabilities of SOM with the robustness of traditional partitioning techniques, optimizing the internal cohesion of the final segments.

The feasibility of clustering for the selected variables was validated using the Kaiser–Meyer–Olkin (KMO) index and Bartlett's test of sphericity, ensuring that the data's correlation structure was suitable for multivariate modeling.

This dimensionality reduction technique employs a neighborhood function to preserve the topological properties of the input space, operating through iterative phases:

1. Competition: For each input vector, neurons compete to be the Best Matching Unit (BMU) based on Euclidean distance.
2. Cooperation: The BMU determines a spatial neighborhood of excited neurons.
3. Adaptation: The excited neurons adjust their weights to reduce distance from the input vector.

This process allows the system to autonomously learn the underlying data structure and group individuals with similar behavioral profiles into adjacent nodes. The model was trained using a dataset of 323 instances and 16 quantitative variables, which were previously standardized to ensure equal statistical weighting across all features. This step is essential to guarantee unbiased Euclidean distance calculations and stable model performance. The network architecture and training parameters were configured as follows:

- Dataset: 323 instances with 16 standardized quantitative variables.
- Grid Size: 10×10 hexagonal neurons (100 total nodes).
- Initialization: Principal Component Analysis (PCA) to ensure global topological ordering and optimize convergence.
- Performance Metric: Quantization Error (QE). An average value of 0.42 was obtained, indicating high precision in instance assignment.

The PCA and training configuration used for the Self-Organizing Map (SOM) consists of: Deterministic PCA weight initialization, Learning rate: 0.5, Neighborhood function: Gaussian, Initial radius (Sigma): 1.5, Training iterations: 1000 (random training), Random seed: 42, and Map topology: 10×10 (100 nodes).

This configuration remained constant throughout the different validation and visualization stages.

The model architecture uses a Self-Organizing Map (SOM) neural network with a 10×10 hexagonal neuron grid, generating an intermediate space of 100 prototype nodes. Performing a second partitioning stage (meta-clustering) on these 100 weight vectors—instead of directly on the 323 raw instances—significantly reduces stochastic noise and preserves the multidimensional topological relationships of the data. Reducing the topology from 100 nodes to 16 final clusters represents an optimal balance that condenses the information without oversimplifying the latent space. The hierarchical meta-clustering was performed using Ward’s method. Mathematically, this criterion seeks to minimize the increase in total variance within the clusters (internal inertia) at each merge step. The increase in the sum of squares between two clusters A and B is defined by the equation:

$$\Delta I(A, B) = \frac{n_A n_B}{n_A + n_B} \|m_A - m_B\|^2$$

where n_A and n_B represent the masses of the clusters, and $\mathbf{m}_A$, $\mathbf{m}_B$ their respective centroids. The selection of 16 clusters corresponds to the optimal cut-off point in the dendrogram where internal inertia remains controlled; a further reduction would cause a drastic loss of internal homogeneity (an abrupt jump in the variance accumulation curve), artificially combining profiles that are theoretically and behaviorally distinct. Data based on psychometric scales of human behavior exhibit high intrinsic variance compared to purely physical or biological variables. A smaller number of clusters (such as traditional, 3 or 4 group approaches) tends to mask highly specific subgroups within the overall averages. To achieve a balance between homogeneity and size, with 16 groups, we ensure that each cluster has a sufficient sample size (most have between 12 and 30 samples) for the mean and standard deviation calculations to be statistically significant. The selection of 16 clusters is statistically supported by the absence of overlap in their 95% confidence intervals for the key dimensions, demonstrating that they do not represent random noise, but rather distinct market realities (scientific literacy versus cultural barriers).

Ward’s method minimizes variance within clusters to preserve topology. By applying it to the SOM weights, we group neurons that are already similar to each other, ensuring that the 16 ‘meta-clusters’ represent clearly differentiated consumer profiles. In this way, 16 is a “sweet spot” that is large enough to reflect market diversity but small enough to make each cluster actionable. The error level in the SOM was measured by Quantization Error, which

measures the average distance between each data point and its Best Matching Unit; lower values indicate better data representation, and Topographic Error measures the proportion of data points for which the first and second BMUs are not adjacent; lower values indicate better preservation of the data's topology.

To validate whether the segmentation is statistically significant, the most appropriate method is to perform a Kruskal–Wallis test [45]. This test considers the effect size (square epsilon) and the significance level (p).

With a final sample of 323 valid instances, a partition into 16 segments guarantees an adequate average sample size per group for performing robust post-hoc descriptive inferences. The optimal balance is verified between the accuracy of the fit (low quantization error) and the commercial interpretability of the identified profiles (acceptance, undecided, and rejection segments).

This work was developed using Python version 3.12.13 (4 March 2026) and R environment via SOMbrero package version 1.5.0.

3. Results

3.1. Statistical Validation and Reliability of the Instrument

The construct validity of the instrument was assessed through an Exploratory Factor Analysis (EFA). The adequacy of the data for factor analysis was confirmed by a Kaiser–Meyer–Olkin (KMO) value of 0.729 and a statistically significant Bartlett's test of sphericity ($\chi = 581.727$, $p < 0.001$), indicating that the correlation structure was appropriate for factor extraction.

Factor extraction was performed using Principal Axis Factoring with Promax rotation, allowing for correlations among latent constructs. The number of factors retained was determined based on eigenvalues greater than 1, scree plot inspection, and theoretical interpretability. The analysis yielded a three-factor solution with eigenvalues of 2.765, 1.505, and 1.028, respectively, explaining 66.23% of the total variance. Communality values ranged from 0.218 to 0.790, indicating an acceptable proportion of shared variance across the retained items. Items with factor loadings greater than 0.40 were considered significant and retained in the final solution.

Cross-loadings were examined and resolved based on theoretical coherence, assigning each item to the factor with the highest conceptual and statistical relevance. Given the use of an oblique rotation method, factor correlations were analyzed.

The results showed moderate relationships between factors, with correlations ranging from 0.23 to 0.48, supporting the assumption that the constructs are related but distinct dimensions of consumer behavior.

The factor structure was interpreted based on the pattern matrix and theoretical coherence of the items:

- Factor 1 (Knowledge of food microorganisms): This factor groups variables V14, V16, and V13, which reflect the level of consumer knowledge regarding microorganisms involved in food preservation. Specifically, it captures awareness of beneficial microorganisms, familiarity with lactic acid bacteria, and understanding of the role of microorganisms in food decomposition. This dimension represents a cognitive component associated with scientific literacy and knowledge of biopreservation processes.
- Factor 2 (Cold Chain Management): This factor includes variables V5, V3, and V2, which are related to consumer practices in handling and storing chicken products. It reflects behaviors associated with refrigeration, freezing, and preservation practices at the household level. This dimension represents operational habits that directly influence food quality and safety after purchase.

- **Factor 3 (Consumer Acceptance):** This factor comprises variables V17 and V15, representing the willingness to purchase chicken treated with biopreservatives and the level of agreement with the use of beneficial microorganisms for preservation. This dimension captures the attitudinal component of consumer behavior toward innovative food technologies.

The complete EFA results, including eigenvalues, communalities, pattern matrix, structure matrix, factor correlations, and scree plot, are provided in Supplementary Materials for detailed examination.

The internal consistency of the instrument and its dimensions was assessed using Cronbach's alpha. The overall scale demonstrated acceptable reliability ($\alpha = 0.702$), supporting the consistency of the instrument in measuring the underlying constructs. The results are summarized in Table 1.

Table 1. Factor loadings and Internal consistency (Cronbach's Alpha).

Factor	Items	Factor Loading	Cronbach's Alpha (α)
Factor 1: Knowledge of food microorganisms	V14	0.887	0.799
	V16	0.761	
	V13	0.628	
Factor 2: Cold Chain	V5	0.743	0.573
	V3	0.526	
	V2	0.453	
Factor 3: Consumer Acceptance	V17	0.727	0.647
	V15	0.658	
Overall instrument Alpha:			0.702

At the factor level, the reliability coefficients showed differentiated behavior:

- **Factor 1 (Knowledge of food microorganisms):** indicating strong internal consistency and a well-defined construct.
- **Factor 2 (Cold chain management):** which, although below the conventional threshold of 0.70, is acceptable given the limited number of items and the exploratory nature of the study.
- **Factor 3 (Consumer acceptance):** reflecting moderate internal consistency, consistent with previous research in early-stage construct validation.

These results are consistent with methodological literature, which supports the acceptability of Cronbach's alpha values above 0.50–0.60 in exploratory studies, particularly when factors are theoretically grounded and contribute meaningfully to explained variance [46].

3.2. Consumer Segmentation and Behavioral Profiles Using SOM

Following the training of the Self-Organizing Map (SOM), the 323 instances were topologically organized into 16 clusters, grouping individuals with similar behavioral patterns.

The final SOM model exhibited a Quantization Error (QE) of 2.21, indicating a precise fit of the instances to their respective winning units (BMUs). Additionally, the Topographic Error (TE) was 0.138, a value that confirms satisfactory preservation of the local topology considering the high dimensionality of the analyzed behavioral variables.

Quantization Error measures the accuracy of the representation. It is the average distance between each real data point and the weight vector of its winning neuron unit (BMU). A value of 2.21 indicates how well the map's prototypes (nodes) represent real consumers. The lower the value, the more closely the node resembles the group of people it

the sum of squares within the clusters when they are combined. A higher cut line would allow for the merging of more heterogeneous groups (fewer clusters).

In the current model, the line is located at $Z[-16, 2]$, which represents the height (distance) on the Y-axis of the dendrogram corresponding to the 16th to the last combination. Drawing a horizontal line at this height visually defines the cut line that separates the data into exactly 16 segments.

In the context of the Z link matrix (calculated using Ward's method), $Z[-16, 2]$ retrieves the cluster merge history, and therefore represents the following:

- **Z (Link Matrix):** This matrix stores the cluster merge history. Each row represents a merge, and the third column (index 2) contains the distance between the two clusters being merged.
- **$[-16]$ (Row Index):** Negative indexing counts from the end. Since the last merge (joining the last two clusters) is in $Z[-1]$, $Z[-16]$ refers to the step where the algorithm decided how to further reduce the data when exactly 16 clusters remained.
- **$[2]$ (Column Index):** Selects the distance value at which that specific merge occurred.

The topology of SOM is shown graphically below, by means of Figure 2, which represents a 10×10 self-organizing map where each hexagon (node) groups consumers with similar behavioral patterns. The map uses a hexagonal topology to preserve spatial relationships between different segments more effectively than a square grid. Each cell is labeled with a cluster ID (C1 to C16), corresponding to the 16 metaclusters identified through hierarchical clustering. The decimal number within each cell represents the average purchase intent (V17) for the samples assigned to that specific node. A color-coding system (traffic light system) has been assigned to clarify the interpretation of purchase intention.

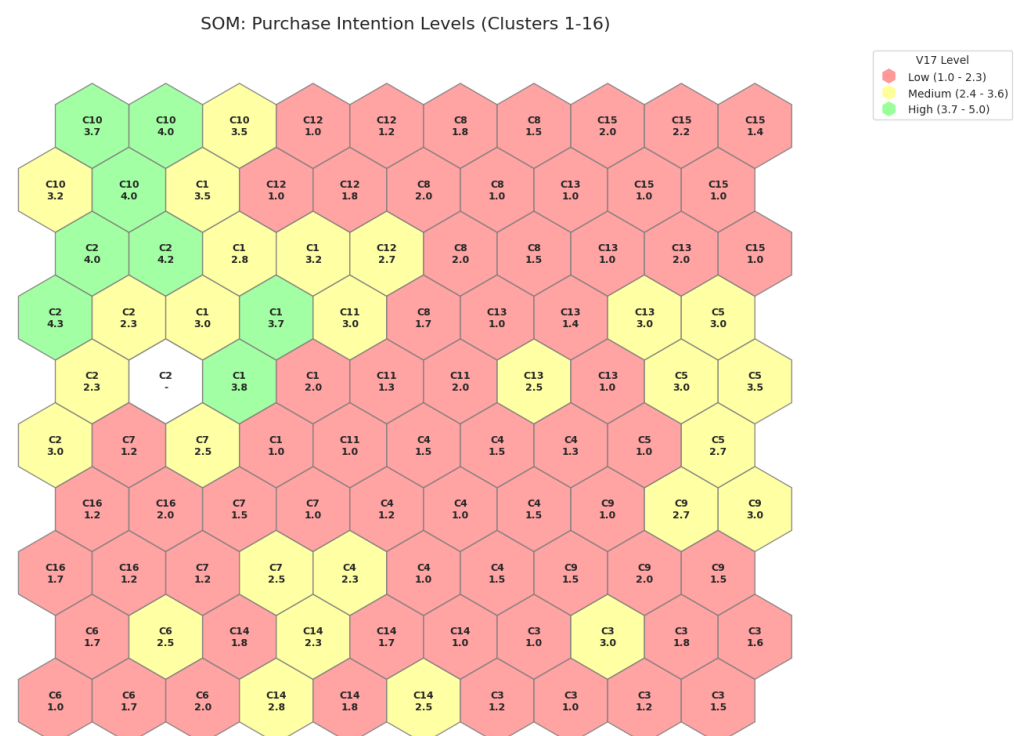


Figure 2. SOM hexagonal map with color scale representing Intention Levels (V17).

The spatial topology is also significant; physically close nodes on the map share similar characteristics. Empty white nodes represent neutral areas where specific consumer samples from the dataset were not mapped during training.

Thus, the map segregates the population: high-value clusters (such as the green nodes associated with Cluster 10 or Cluster 1) are concentrated in specific regions, allowing for the development of targeted marketing strategies based on the specific characteristics of those areas. The color thresholds used to interpret the target variable are summarized in Table 2.

Table 2. Interpretation criteria and color coding used for purchase intention (V17) levels in the SOM visualization.

Color	V17 Level	Interpretation
Green	High (>3.7)	Represents the consumer segments with the highest probability of purchase. These are the “star” clusters.
Yellow	Medium (2.4–3.6)	Segments with moderate intent. They could be persuaded with promotions or product adjustments.
Red	Low (<2.3)	Groups that show little or no interest in purchasing the product based on the analyzed variables.

The descriptive analysis of the clusters revealed highly differentiated consumer profiles. Table 3 summarizes the count, mean, and standard deviation for each of the 16 clusters based on variable V17 as a passive variable. For each of the clusters, aggregate descriptive statistics of this latent variable are calculated:

- Mean (μ): The average purchase willingness of that specific group.
- Standard Deviation (σ): The level of internal consensus of the response within the group.
- Confidence Intervals (95%): The statistical ease to verify that the groups really differ from each other in their purchase intention.

Table 3. Cluster analysis results (V17 projection)

Cluster	Count	Mean	Std. Dev.	CI Lower (95%)	CI Upper (95%)
1	30	3.10	1.12	2.68	3.52
2	19	3.26	1.41	2.58	3.94
3	28	1.46	0.74	1.18	1.75
4	26	1.46	0.76	1.15	1.77
5	16	2.69	1.35	1.97	3.41
6	20	1.65	1.04	1.16	2.14
7	22	1.59	0.91	1.19	1.99
8	19	1.74	0.87	1.32	2.16
9	15	1.93	1.22	1.26	2.61
10	18	3.56	1.29	2.91	4.20
11	14	1.93	1.21	1.23	2.63
12	16	1.56	1.09	0.98	2.15
13	21	1.71	0.96	1.28	2.15
14	26	2.12	1.11	1.67	2.56
15	19	1.53	0.84	1.12	1.93
16	12	1.42	0.67	0.99	1.84

In order to analyze whether the proposed clusters correctly segment the database, Silhouette score was calculated. The silhouette analysis for the 16-cluster solution yielded an average silhouette score of 0.1958, with the cluster-level values summarized in Table 4. The differences in Silhouette values have a direct impact on the reliability and strategic use of each segment.

Highly Reliable Segments (e.g., Clusters 1 and 10) are those with Silhouette values close to 0.30–0.35; these groups are the purest. Strategic decisions made for these clusters

(such as those with high purchase intent) carry less risk, since the consumers within them behave very similarly to each other and are quite distinct from others.

Table 4. Silhouette analysis for the 16-cluster solution.

Cluster	Silhouette
1	0.080159
2	0.122868
3	0.220909
4	0.181423
5	0.103457
6	0.191287
7	0.162393
8	0.203996
9	0.347237
10	0.298656
11	0.252787
12	0.264552
13	0.154147
14	0.170215
15	0.223511
16	0.282592

Transition segments (e.g., Cluster 1), with a low value (0.08), indicate that this group is on the border between several profiles. This means that customers in Cluster 1 could respond unpredictably or easily migrate to other segments. These groups require closer monitoring or a more flexible offering.

The fact that the average is 0.19 confirms that segmentation is useful but that the market is a continuum. Instead of completely isolated groups, the data set contains groups with characteristics that gradually transform, which is common in human behavior data.

The hierarchical meta-clustering solution yielded a Calinski–Harabasz (CH) index—or Variance Ratio Criterion—of 13.22. In unsupervised machine learning applied to consumer psychology and behavioral sciences, absolute CH values tend to be lower than those observed in physical or geometric datasets. This is attributed to the inherent psychometric noise and continuous nature of human behavioral data, where consumer attitudes exist along a spectrum rather than as perfectly isolated entities.

The formula for the CH index is defined as follows:

$$CH = \frac{\text{Tr}(B_k)/(k-1)}{\text{Tr}(W_k)/(n-k)}$$

where $\text{Tr}(B_k)$ and $\text{Tr}(W_k)$ represent the trace of the between-cluster and within-cluster scatter matrices, respectively, for k clusters and n instances. Because our model prioritizes a granular, high-resolution segmentation ($k = 16$), the denominator $(k - 1)$ naturally decreases the absolute index score. However, a CH index of 13.22, coupled with the highly significant Kruskal–Wallis test ($p < 0.001$, $\varepsilon^2 = 0.29$) and a positive average Silhouette score (0.19), confirms that the 16-cluster partition successfully captures mathematically valid and strategically meaningful transitions across a complex consumer continuum.

Together with the Silhouette value (0.19), the CH index confirms that the clusters are not isolated (they are not ‘clouds’ separated by emptiness), but are part of a continuous map of consumers where the boundaries are subtle but statistically valid.

Based on the statistical results obtained (Table 3), the clusters with the highest acceptance (Purchase Intention V17) can be presented based on two criteria. Cluster 10 (High-Acceptance Exploratory Segment) has the highest mean (3.56). Although its count is moderate (18 people), its Confidence Interval [2.91, 4.20] indicates that even in the most

pessimistic scenario, its acceptance is higher than most of the other groups. It represents the segment with the highest observed purchase intention within the study sample. Cluster 2 (moderate-to-high acceptance segment) has a mean of 3.26. What makes it attractive is its upper limit of the CI (3.94), suggesting that there are individuals with very high purchase intention in this group, although its standard deviation (1.41) indicates greater heterogeneity than other groups. Cluster 1 (Consistency) has a mean of 3.10 and the highest count among the top groups (30 people), offering the most stable volume. Its standard deviation (1.12) is lower than that of Cluster 2, making it a more predictable segment.

Therefore, it can be summarized that Cluster 10 is statistically superior to the low-acceptance clusters (such as 16, 4, or 3), since their confidence intervals do not overlap. Therefore, if volume is the goal, Cluster 1 exhibited the largest number of consumers among the higher-acceptance groups, whereas Cluster 10 showed the highest mean purchase intention score.

To complete the statistical profile of the consumer segments, Figure 3 presents a comparative bar chart showing the average purchase intent (V17) for each group. The 95% confidence intervals are included as error bars to clarify the statistical significance of each group.

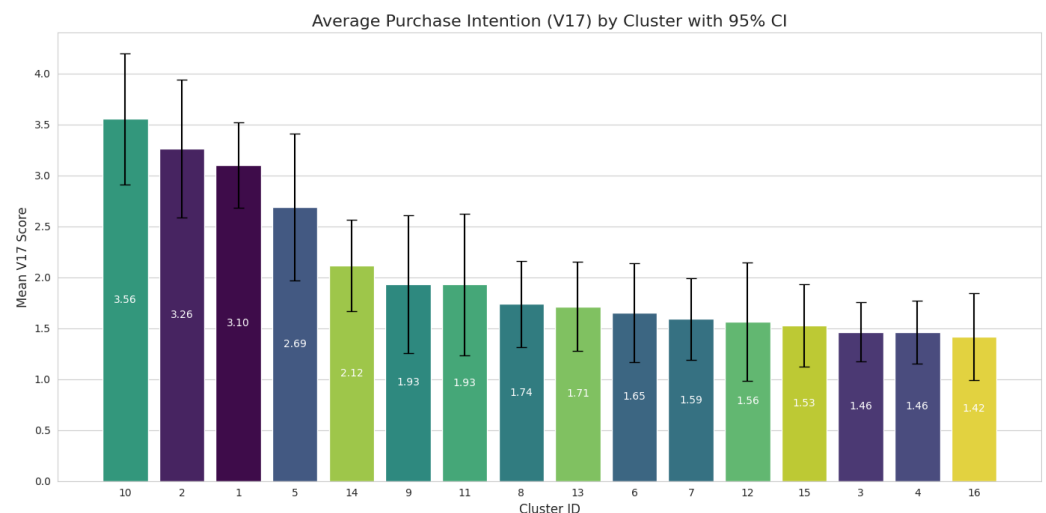


Figure 3. Average purchase intention (V17) by consumer cluster with 95% confidence intervals.

At the top level (Groups 10, 2, 1), bars clearly stand out due to their higher scores. The error bars (confidence intervals) for these groups are higher than those of the others, confirming their higher purchase intention scores. While Group 10 has the highest mean, its error bar is slightly wider than that of Group 1, which has more samples and, therefore, a more stable (narrower) interval. A large number of clusters (such as 16, 4, 3, and 15) are grouped at the bottom of the chart with means below 2.0, representing the segments with the lowest purchase intent.

Additionally, purchase intention (V17) is correlated with the other variables in the dataset to understand which specific factors or behaviors most strongly drive consumer interest.

Pearson's linear correlation analysis reveals which factors are most associated with Purchase Intention (V17). The most relevant findings are based on the degree of correlation between variables, as shown in Figure 4.

- Strong Positive Correlations: V15 (0.67) has the greatest influence. There is a strong, positive linear relationship; as V15 increases, purchase intention increases significantly.
- V14 (0.47) has a moderate-to-high correlation, making it the second most important driver of purchase intention.

- **Weak Correlations:** Variables such as V16 (0.22), V13 (0.19), and V5 (0.16) show a positive but much more subtle influence.
- Variables such as V2, V1, and V4 have practically no linear relationship with purchase intention (values close to 0).
- **Negative Correlations:** V7 (-0.12) is the only variable with a perceptible negative correlation, suggesting that high levels in V7 might be slightly associated with lower purchase intention.

To increase purchase intention (V17), V15 and V14 were identified as the variables most strongly associated with purchase intention in this dataset on optimizing or incentivizing the aspects measured by V15 and V14, as these are the most robust predictors in this dataset.

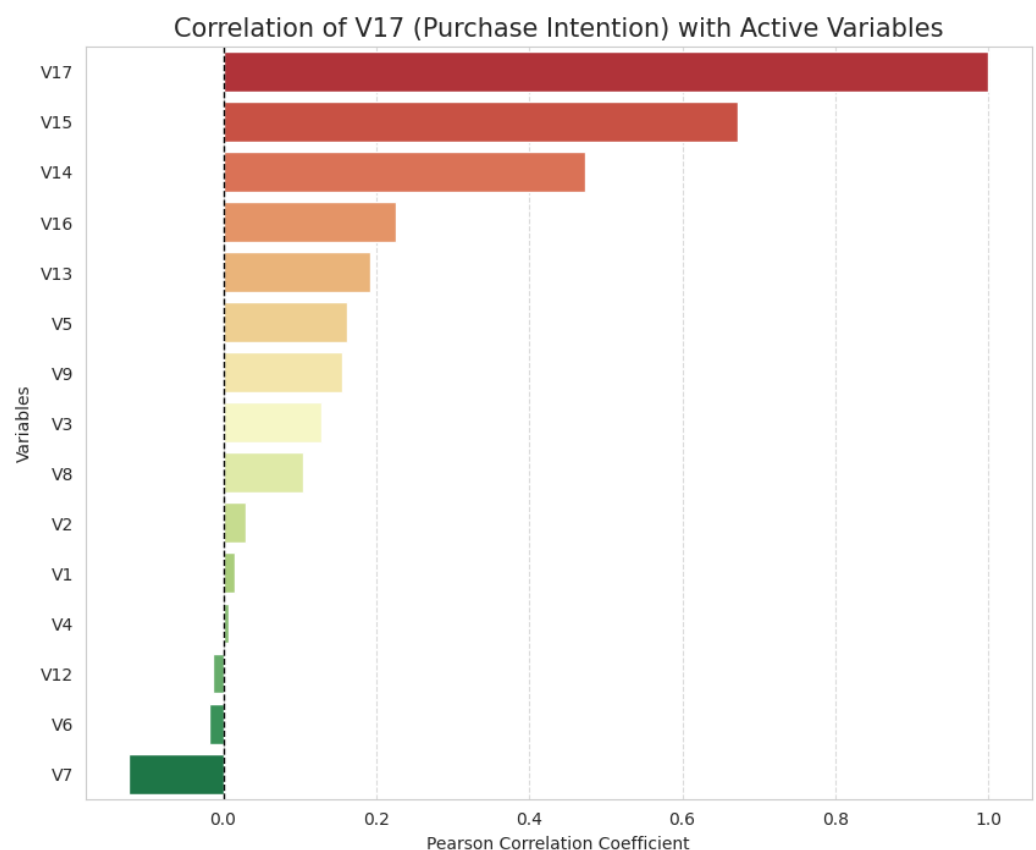


Figure 4. Pearson correlation coefficients between purchase intention (V17) and the behavioral variables analyzed in the study.

This group is characterized by a lack of perceived knowledge, with very low scores in awareness of beneficial microorganisms (V14 = 1.20) and familiarity with lactic acid bacteria (V16 = 1.40). In addition, they exhibit inadequate household practices that compromise food safety, including a strong tendency toward cross-contamination, such as washing raw chicken before cooking (V12 = 4.60). These findings suggest that both knowledge gaps and entrenched cultural practices act as significant barriers to the acceptance of technology.

3.3. Intermediate Segments and Market Opportunities

Beyond the extreme clusters, the SOM analysis identified intermediate segments representing potential market opportunities, particularly clusters G12 and G8, which exhibited moderate or uncertain purchase intention (V17 = 3.10 and 3.30, respectively). Consumers in these segments demonstrate strong purchasing and handling behaviors, including a preference for refrigerated chicken (V2 = 4.80) and consistent verification of expiration dates (V9 = 5.00). However, despite these favorable practices, they display limited knowledge

of biopreservation, with low awareness of lactic acid bacteria ($V16 = 1.21$) and minimal understanding of the role of beneficial microorganisms ($V14 = 1.89$).

3.4. Behavioral Pattern Analysis Across Clusters

The cluster analysis revealed consistent patterns in consumer habits and perceptions. Variables V17, V15, V14, and V16 were identified as the highest-rated across the selected groups, corresponding to product disposal due to quality concerns, expiration date verification, and knowledge and acceptance of beneficial microorganisms. Conversely, the lowest-rated variables were V6, V12, and V4, indicating low preference for frozen chicken and a relatively low frequency of encountering spoiled or visibly damaged products among respondents. The complete set of quantitative variables used for SOM training and cluster characterization is presented in Table 5.

Table 5. Description of the quantitative variables used in the study.

Code	Variable Description
V1	Importance of chicken cost in the purchase decision.
V2	Preference for refrigerated chicken at the time of purchase.
V3	Preference for frozen chicken at the time of purchase.
V4	Storage of chicken in the refrigerator upon arriving home.
V5	Storage of chicken in the freezer upon arriving home.
V6	Experience of having purchased spoiled chicken.
V7	Discards chicken if the expected quality is not perceived.
V8	Identification of visible lesions on the purchased chicken.
V9	Frequency of checking or asking for the expiration date.
V11	Concern about purchasing products without a TIF (Federal Inspection Type) seal.
V12	Practice of rinsing chicken with water before cooking.
V13	Knowledge that microorganisms influence fresh chicken decomposition.
V14	Knowledge of “good” microorganisms that help preserve food.
V15	Agreement with using “good” microorganisms to preserve chicken.
V16	Awareness of Lactic Acid Bacteria (LAB) as natural preservatives.
V17	Willingness to buy chicken treated with LAB for enhanced freshness and safety.

Note: The variables were measured using a five-point Likert scale (1–5), where higher values indicated greater agreement, frequency, preference, concern, or perceived knowledge depending on the item.

4. Discussion

4.1. Synergy Between Theoretical Factors and Machine Learning

The three-dimensional structure identified through Exploratory Factor Analysis (EFA) not only provided statistical validation of the instrument but also established a conceptual framework for interpreting the topology of the Self-Organizing Map (SOM).

The three-factor structure identified through EFA provides a robust conceptual framework that supports the interpretation of the SOM-based segmentation.

The overall internal consistency obtained ($\alpha = 0.702$) supports that these dimensions adequately capture the complexity of consumer behavior.

According to [41], stochastic variants of SOM enable the visualization of high-dimensional data while preserving its topological structure. In this study, the findings suggest that consumer acceptance is strongly associated with knowledge of food microorganisms and biopreservation processes. This highlights the role of scientific literacy as a key driver of trust in emerging food technologies [20].

4.2. From Traditional Statistics to Machine Learning

The application of SOM-based clustering allowed us to overcome key limitations of conventional descriptive statistical approaches. As noted by [40], SOM-based segmentation is more effective than traditional partitioning methods because it enables the identification

of highly specific behavioral subgroups that are often masked in global averages. This methodological advantage enabled the identification of cluster G16 as a low-acceptance exploratory segment strongly associated with low levels of scientific literacy. These findings are consistent with previous research highlighting the role of consumer perceptions in shaping attitudes toward food technologies [39]. Conversely, the identification of the high-acceptance exploratory segment (Cluster 10) revealed that attributes such as freshness and Knowledge of food microorganisms outweigh price considerations as primary determinants of purchase intention. This insight is particularly relevant in the context of global food security challenges, where consumer trust in product quality becomes a critical factor for market resilience [2].

These findings are consistent with the factor structure, particularly the role of knowledge (Factor 1) and behavioral practices (Factor 2) in shaping consumer segmentation.

Unlike traditional statistical approaches based on global averages, SOM-based segmentation captures the behavioral heterogeneity of consumers and preserves the topological structure of multidimensional data. This allows the identification of distinct acceptance profiles that would otherwise remain hidden within aggregated statistics, providing deeper insights into the relationship between microbiological knowledge, consumer perceptions, and willingness to adopt biopreservation technologies.

4.3. Opportunity Segments and Cultural Barriers

The analysis also identified intermediate segments, such as clusters G12 and G8, representing consumers with moderate or uncertain purchase intention. These individuals exhibit strong cold chain management practices but show low acceptance of biopreservation technologies, primarily due to a lack of technical knowledge. This finding suggests that resistance to innovation is not necessarily driven by negative attitudes, but rather by informational gaps. Therefore, these segments represent a potential group for further validation for targeted educational interventions. On the other hand, the behavioral patterns observed in cluster 10 indicate the presence of deeply rooted cultural practices that may hinder food safety and the adoption of technology. For instance, the frequent practice of washing raw chicken ($V_{12} = 4.60$) reflects misconceptions about hygiene that may increase the risk of cross-contamination. As highlighted by [8], improper domestic handling practices are among the weakest links in the food safety chain, reinforcing the idea that consumer education is essential not only for technology adoption but also for risk mitigation.

4.4. Implications for Commercial Implementation

From a practical perspective, the findings suggest that from a practical perspective, consumer heterogeneity may be relevant when exploring future communication and market positioning strategies for biopreservatives in the meat industry. Successful implementation requires consumer education efforts that clearly communicate the role of lactic acid bacteria as beneficial microorganisms capable of inhibiting common spoilage agents such as *Pseudomonas* spp., which are responsible for enzymatic and sensory deterioration in refrigerated meat products [7,15].

The identified factors provide actionable dimensions for designing targeted communication strategies, particularly by strengthening consumer knowledge of biopreservation mechanisms.

Furthermore, informative labeling that emphasizes freshness and biopreservation-related knowledge (Factor 1) is a promising approach for building trust among undecided consumers. Positioning biopreservation as a natural and safe technology may facilitate its acceptance, particularly among consumers already concerned with product quality.

The consumer segments identified in this study should be interpreted as exploratory profiles derived from the analyzed sample. Further validation using larger and more diverse consumer populations is required before generalizing these findings or deriving market-wide commercial recommendations. Nevertheless, the results provide useful insights for generating hypotheses regarding the factors that may influence consumer acceptance of biopreservation technologies.

Consumer interest in emerging technologies in poultry production increases when these are associated with sustainability, safety, and health benefits. Other authors reported that 83.7% of consumers were willing to purchase chicken produced using innovative technologies, and that this acceptance was influenced by factors such as educational level, sustainability beliefs, and prior consumer knowledge, highlighting the importance of consumer perception in the adoption of emerging strategies [47], such as the biopreservation approach proposed in the present study.

A limitation of the present study is that the sample was obtained through convenience sampling in a single Mexican city. Therefore, the identified consumer profiles should not be considered representative of the Mexican population or of emerging markets as a whole. Future studies involving probabilistic sampling strategies and geographically diverse populations are needed to evaluate the generalizability of the findings.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16136552/s1>; Table S1. Total variance explained obtained through Principal Axis Factoring. Table S2. Communalities of the variables retained in the Exploratory Factor Analysis. Table S3. Pattern matrix obtained after Promax rotation with Kaiser normalization. Table S4. Structure matrix showing factor loadings and factor-variable relationships. Table S5. Factor correlation matrix obtained from the oblique rotation procedure. Figure S1. Screen plot used to determine the number of factors retained in the Exploratory Factor Analysis.

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