Prabha Materials Science Letters
Vol. 5, No. 1, 103-122, 2026
https://doi.org/10.33889/PMSL.2026.5.1.006

Computational Analysis for Health-Tech Products: A Study for Water Ionizers

Saurabh Pandey
Department of Management,
University School of Management and Entrepreneurship (USME),
Delhi Technological University, 110095, Delhi, India.
E-mail: saurabhpandey_2k20phdusme04@dtu.ac.in

Deepti Aggrawal
Department of Management,
University School of Management and Entrepreneurship (USME),
Delhi Technological University, 110095, Delhi, India.
Corresponding author: deeptiaggrawal@dtu.ac.in

(Received on October 22, 2025; Revised on January 12, 2026 & February 2, 2026; Accepted on February 3, 2026)

Abstract
The increasing popularity of water ionizers in the health and wellness marketplace is attributed to the health benefits of electrolyzed reduced water (ERW) among consumers. These devices enrich water quality by increasing the pH and providing antioxidants. This study examines consumer preferences in the Indian water ionizer market using conjoint analysis and K-means clustering to assist businesses in developing and benchmarking product offerings and targeted marketing strategies, leveraging purchase decisions, and consumer segmentation. To quantify the importance of attributes using conjoint design, a survey of 479 respondents was conducted based on five key attributes: brand, pH type, price, oxidation-reduction potential (ORP), and annual maintenance cost (AMC). K-means clustering is applied to segment consumers into homogeneous groups based on their preference patterns and decision-making behaviours. Conjoint analysis revealed that pH type and brand were the most influential attributes, followed by price, ORP, and annual maintenance cost. K-means clustering identified four distinct consumer segments: AMC-sensitive, pH-sensitive, price-sensitive, and brand-loyal consumers. The data-driven framework for benchmarking consumer preferences and segmenting markets provides comprehensive insights for businesses to achieve more promising market penetration and customer satisfaction by addressing diverse consumer needs.

Keywords- Conjoint analysis, Consumer behaviour, K-means clustering, Market segmentation, Water ionizers.

1. Introduction

The water ionizer market refers to a niche segment in the ionizer industry, where the target segment is health-conscious individuals irrespective of their income class in society. Water ionizer devices that alter the chemical composition of water, such as pH and oxidation-reduction potential (ORP), have seen growing sales worldwide in recent years as consumers become increasingly health conscious. Devices modify water pH using a method called electrolysis, which has been promoted for purported health benefits, such as increased hydration, detoxification, and antioxidant effects. Various attributes and their relationships have been identified, which are important for the adoption of water ionizers (Pandey & Aggrawal, 2025a). These machines have become increasingly common, with health-conscious consumers seeking ways to improve their general health by improving water quality. There is an increasing trend worldwide towards participation in activities that fall under the umbrella of health and wellness. The demand for these products is primarily motivated by consumers' attempts to maintain their health, look younger, and promote overall well-being. When drinking water is consumed with ions, it permeates cell membranes to maintain fluid balance and provide more energy, serving the cell's interests. In such a business scenario, where there is an increasing trend of consumers towards health-related products, it becomes imperative to understand consumer decision-making as it helps to understand consumer behaviour and forms the basis of a marketer's business strategies. Consumer behaviour refers to the buying habits of consumers, their attitudes, and other internal and external factors that affect their choice of products or services (Roberts & Pirog, 2004).

Water is a concern for everyone, and the study of consumer behaviour in the water ionizer industry is a compelling area of study that delves into every aspect of business marketing, including sales, relative industry analysis, and strategic decision-making (Lewin & Donthu, 2005). It investigates the processes of selecting, consuming, and disposing of products, services, experiences, or ideas to satisfy needs, as well as the impact individuals or groups have on products (Tseng, 2014). The investigation of consumer logic and actions to scrutinize and understand consumers' choices is important and is currently being studied more by industry, which is directly affected by consumers' perceptions (Foxall, 2005). Regarding consumer behaviour, buyers' demographic characteristics have a certain degree of relevance to the buying process of advanced technological devices (Josiassen et al., 2011). The development of products tailored to specific geographical segments is crucial for manufacturers. Research on geographical market segmentation not only helps estimate market potential but also enables manufacturers to understand consumer attribute preferences across regions when choosing water ionizers.

The motivation behind this study lies in the limited empirical understanding of how consumers evaluate product attributes and make trade-offs when selecting water ionizers in the Indian market. Despite their increasing popularity, there remains a gap in understanding how consumers evaluate and prioritize product attributes in this niche market. This study aims to bridge that gap by applying conjoint analysis and K-means clustering to uncover nuanced consumer preferences and segment-specific behaviours. The objective is not only to quantify attribute importance but also to derive actionable insights that can guide product development, pricing, and marketing strategies in the health-tech domain.

To achieve this, the study contributes a hybrid methodological framework that integrates choice-based conjoint analysis with unsupervised clustering, offering a robust approach to market segmentation. This dual-layered analysis enables the identification of distinct consumer segment such as price-sensitive, brand-loyal, and pH-conscious buyers where each with unique decision-making patterns. From a marketing theory perspective, the study builds upon foundational concepts in consumer behaviour, segmentation, and value-based marketing. It draws on the Health Belief Model (HBM) and Theory of Planned Behaviour (TPB) to explain the psychological and behavioural drivers behind product adoption. Furthermore, the use of conjoint analysis aligns with expectation theory and utility-based decision-making, while K-means clustering supports the theory of market heterogeneity and targeted marketing. These theoretical underpinnings strengthen the study's relevance to marketing scholars and practitioners seeking to understand how consumers make trade-offs among competing product features.

Conjoint analysis is a modern strategy used by industries to build service items that best match customer preferences, using different qualitative and quantitative assessment approaches (Rao, 2014). When a decision is difficult and many characterizations are available with several features and improvements, such as purchasing and checking the features, conjoint is the most powerful system for product attribute feature analysis. Whether someone buys a new automobile, a family is searching for a holiday house or newly installed belongings in communities or workplaces, which helps solve complicated, composite, or multifaceted decisions. K-means clustering is a spontaneous unsupervised learning strategy that is used to segment nested data into clusters. Segmentation depends on purposeful attributes including consumer and market features. In the market for organic food, pure water, and other consumer goods industries (Facendola et al., 2023), k-means has generated promising outcomes. Conjoint and clustering techniques help identify

distinct consumer segments (Green & Krieger, 1991), enabling marketers to tailor product attributes and improve purchase intention through segment-specific strategies (Do Paco et al., 2009).
This study aims for adoption patterns, measured in terms of the ranking of the attributes, to signify the following objectives:

- To determine the product ranking that influences consumer preferences for water ionizers in the Indian market.
- To segment markets based on consumer preferences and behaviours using conjoint analysis and K-means clustering analysis.

The literature on sustainability, water ionizers, their health benefits, and consumer behaviours is presented in Section 2. In Section 3, the research methodology presents variables affecting the uptake of these technologies and the joint analysis and K-mean clustering technique used in this study. Section 4 explains the details of the joint analysis; consequently, the K-means clustering analysis is discussed in Section 5. The discussion and managerial implications are presented in Sections 6 and 7, respectively, followed by the conclusion, study limits, and future directions on the intricate web of factors impacting consumer views of the sustainable adoption of water ionizers in Section 8.

2. Literature Review and Building Blocks of the Present Study

Existing literature on the water technology sector highlights the growing market potential of water ionizers and examines the factors influencing consumer acceptance of such technologies. Prior studies show that adoption decisions are shaped by perceived health benefits, cost-effectiveness, and the alignment of these technologies with sustainable living practices (Pandey & Aggrawal, 2024). Research also demonstrates that conjoint analysis and K-means clustering provide robust tools for understanding consumer preferences, enabling businesses to derive data-driven insights that inform product design, marketing strategies, and customer satisfaction initiatives.

The sustainability of ionized water depends on the efficiency of the electrolysis process used by water ionizers to separate water into alkaline and acidic streams, which influences both product quality and environmental impact. Many studies have not explored sustainable features of healthy water consumption. This study is critical for identifying consumer behaviour toward the adoption of sustainable sources of healthy water, which concerns the precise adoption of healthy water consumption for human life. Sustainable activities must incorporate convenience and practicality into daily life. Consumers evaluate product sustainability based on maintenance requirements, usability, and the ease of integration into their daily routines (Vodounon et al., 2022). Research suggests that alkaline water may support health and longevity, whereas acidic water has been linked to adverse effects (LeBaron et al., 2022). Alkaline water is also noted for added properties such as improved taste, food preservation, and certain sanitary and cosmetic uses.

The health benefits of water ionizers and sustainability outline consumer perception and behaviour based on the Health Belief Model (HBM) and Theory of Planned Behaviour (TPB). **Figure 1** shows the influence of consumer adoption perception based on HBM and TPB.

The HBM is a prominent health behaviour theory aimed at predicting and explaining health behaviours (Yastica et al., 2020). Water has known therapeutic properties, and the consumption of water with different pH values affects physiological processes and can prevent, mitigate, or rehabilitate diseases. In conjunction with certain unprecedented technologies, "alkaline ionized water" has emerged as commercial water purported to exert specific biological effects well beyond those of ordinary water. Hydration, antioxidant qualities, alkalinity, detoxification, and improved digestion are some of the possible health advantages of alkaline ionized water (AIW) produced by water ionizers (Henry & Chambron, 2013). Reduced water has been demonstrated to control oxidative stress-related illnesses, including diabetes, cancer, arteriosclerosis, neurological diseases, and hemodialysis side effects (Shirahata et al., 1997).

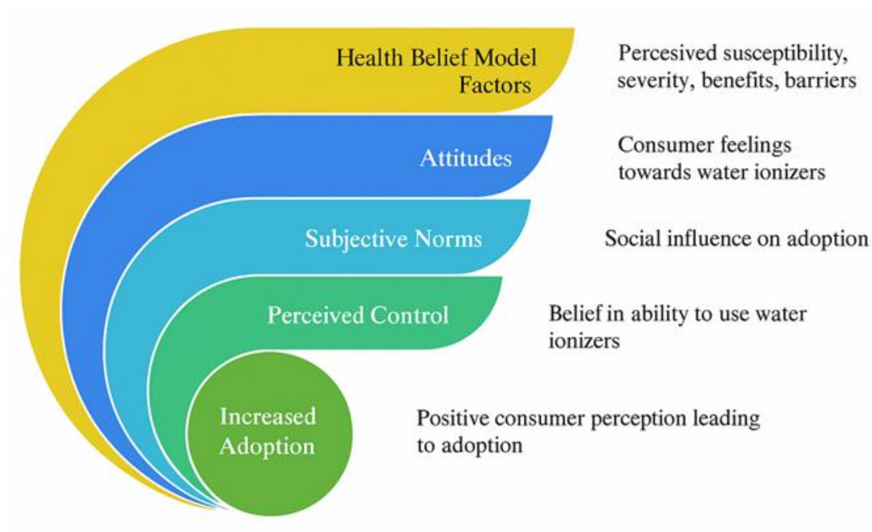

Figure 1. Adoption theory based on HBM and TPB.

Below **Figure 2** unveils the interdependence between the adoption using HBM and TPB.

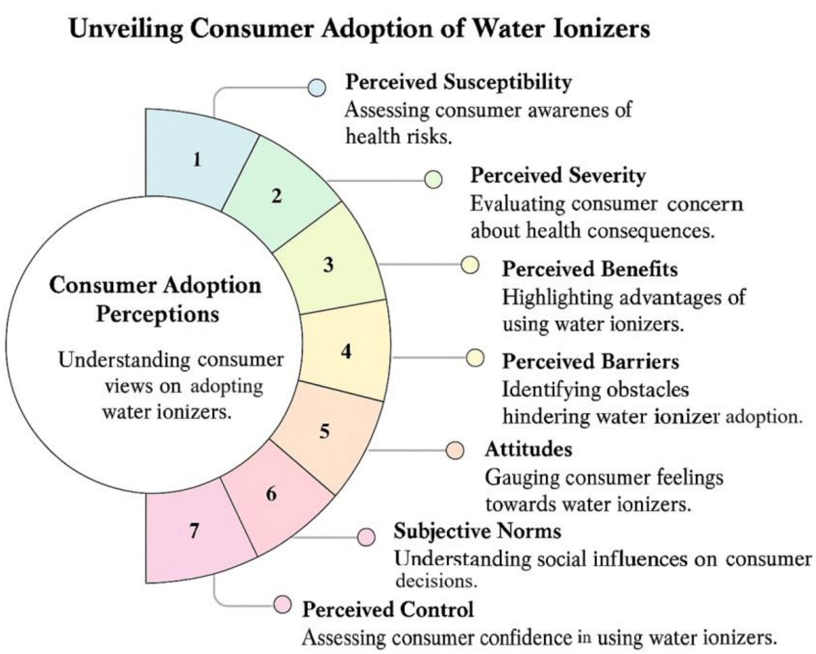

Figure 2. Unveiling the adoption using HBM and TPB.

Past studies applying HBM and TPB to health-tech adoption highlight that perceived benefits, behavioural intentions, and demographic factors shape consumer evaluations of product attributes such as functionality, brand, and price (Zhang et al., 2017). This analytical technique has been employed to produce a range of strategies that support customer segmentation by identifying particular consumer requirements that attain benefits and improve sales predictions (Anand et al., 2018) and customer loyalty (Suhartanto et al., 2024). The outcomes that determine the proportion of features indicate the preferences of various products involved in a particular customer in different portfolios (Johnson & Selnes, 2004). K-means cluster analysis can also distinguish between several sets of related individuals based on their choice (Kodinariya & Makwana, 2013). Consumer preferences and choices depend on the individual and product attributes. Thus, conjoint analysis assesses consumer decisions and identifies segments that program a set of stipulations. Clusters sufficiently large to be targeted must be predetermined. This conjoint analysis and K-means cluster analysis offer insights into the hidden relationships between the class and preference spectra in the water ionizer market. Unveiling a set of features valuable to consumers could help marketers pinpoint what they need to select from among the products they study.

Consumer behaviour can be explained by individual, social, and environmental factors (Dahl, 2013). Consumers prioritize the safety, taste, and smell of tap water, and concerns about contamination have eroded trust in municipal supplies (Bruvold et al., 1975). This loss of confidence has increased the use of bottled water, reverse osmosis systems, and home filtration devices. Following COVID-19, interest in ionized or 'healthy' water has grown rapidly in the Indian market, reflecting consumers' willingness to spend more for better water quality (Pandey & Aggrawal, 2025b) and underscoring the need for water utilities to consider consumer preferences in their management practices. The limited literature on consumer behaviour and perception instigates this study to understand TPB in conjunction with HBM for water ionizers.

Consumers make decisions based on the results of an evaluation study that relates not only to the product itself but also to the environment of consumer activity (Axsen & Kurani, 2012). This study covers three main theories that explain the factors that affect consumer behaviour. The first of these theories came from psychology. According to this theory, consumer behaviour is influenced by psychological factors related to the role of people in shaping their personalities as well as social attitudes, religious beliefs, customs, etc. (Mathras, et al., 2016). The second theory is derived from a sociocultural perspective. According to this theory, behaviour is influenced by socialization, the process by which people learn about their culture and become members of society (Grusec & Davidov, 2010). Suggestions from family, friends, neighbours, colleagues, experiences, and acquaintances have proven valuable in determining the pace and most effective patterns of influence on consumer behaviour. The third theory is derived from economics, which divides consumer attitudes based on specific rational decision-making processes (Chater et al., 2010), starting from the pleasure that all consumers seek to satisfy their needs through limited pricing. Their behaviour in purchasing goods is rational and interrelated with their position and purchasing power.

Classical theories of consumer behaviour do not rule out that consumption is driven not only by basic needs but also by wants (Nelson & Consoli, 2010). There is another utilitarian view of consumers' needs. In this respect, consumer buying behaviour is influenced by whether consumers meet fewer or more than their basic needs (Hausman, 2000), which determines the difference between higher social needs and individual needs. Use is determined by individual self-interest, and each self-expression of interest can be tailored to maximize personal interests that society can recognize (Kan & Fabrigar, 2020), which, in turn, motivates individuals to achieve their needs, which range according to hierarchy.

Previous research demonstrates that conjoint analysis is a robust approach for measuring consumer trade-offs among product attributes, while clustering techniques such as K-means help identify heterogeneous preference patterns across market segments (Ong et al., 2023). Together, these methods offer a structured way to model complex consumer evaluations and have been applied in multiple product and service categories to support segmentation, product design, and targeted marketing strategies.

3. Research Methodology

Data-driven techniques have been used to segment respondents into homogeneous groups based on their preference patterns. The application of conjoint analysis in marketing research has been validated in various domains, including cause-related marketing, where it effectively captures consumer preferences for hedonic products (Kulshreshtha et al., 2019). This supports its relevance in analysing healthcare products, such as water ionizers. It helps determine the relative importance of various attributes and their levels in influencing consumer decision making. By presenting respondents with a set of product profiles composed of different attribute combinations, conjoint analysis enables researchers to discern the preferences and trade-offs consumers are willing to make.

This methodology combines quantitative techniques to provide insights into consumer behaviour and preferences. **Figure 3** depicts the process flow at a higher level, which was used in this study.

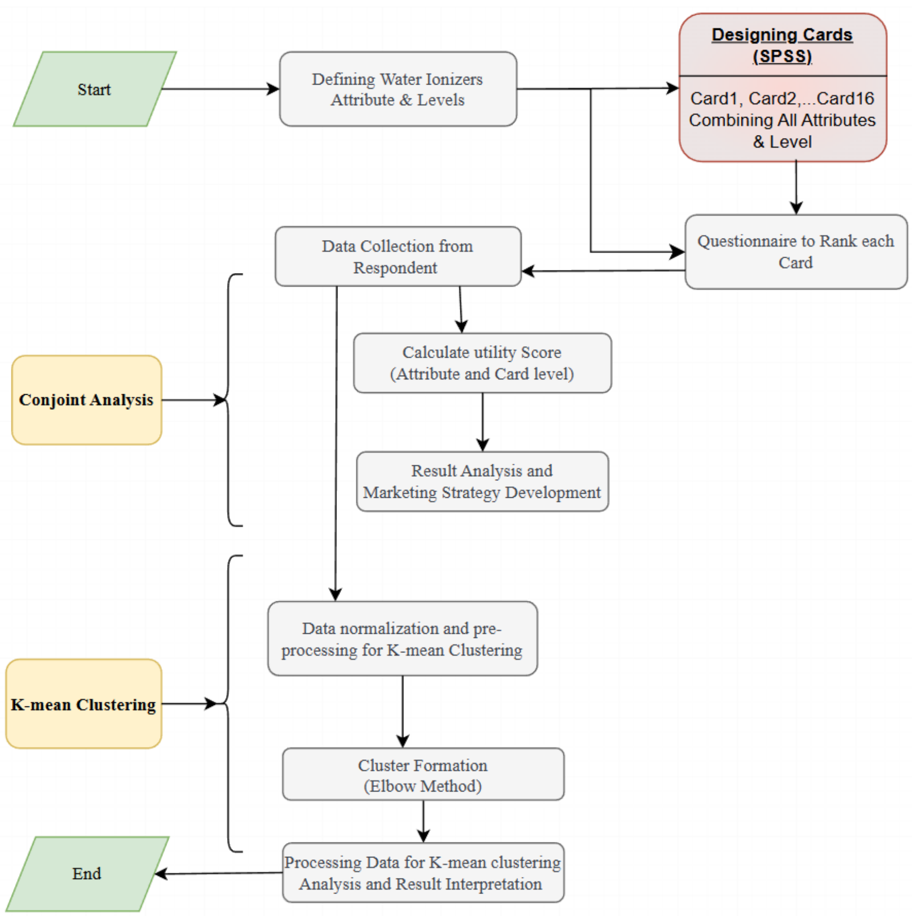

Figure 3. High-level methodology.

3.1 Conjoint Analysis

Conjoint Analysis is a statistical technique used in marketing to understand consumer preferences and choices of consumers (Louviere, 1994). It quantifies the importance that consumers place on different features of a product and provides an essential tool for predicting responses to new product design. Its variants have become the method of choice for quantitative preference measurement and are considered among the significant contributions (Netzer et al., 2008) of marketing science. This study integrates conjoint analysis to optimize product features by combining customer preferences and perceptions to demonstrate the utility of core and optional attributes in guiding product features to maximize overall customer satisfaction (Wang & Wu, 2014). These experiments ask a participant, typically a consumer, to make a trade-off between possible product profiles (Lewis et al., 1991). In conjoint design, product profiles are constructed by combining attributes at different levels. The resulting choices allow researchers to quantify part-worth utilities and determine how respondents trade off specific product features. This approach simulates realistic decision-making environments and provides a structured way to identify the attribute combinations and price levels that consumers value most. Conjoint analysis provides predictions and can simulate consumer purchasing behaviour (Backhaus et al., 2007). However, conjoint analysis has limitations, particularly when respondents are required to evaluate many full-profile combinations, which may increase cognitive burden and lead to less reliable responses. To ensure the validity of the conjoint design, the attribute list and level combinations were first reviewed through a small pre-test to confirm that respondents could understand the options and found them realistic. In addition, the significance of all attributes in the ANOVA results ($p < 0.05$) offers evidence that each attribute contributed meaningfully to the overall preference model.

3.2 Clustering Analysis

K-means clustering is a data-driven unsupervised machine-learning technique for cluster analysis that partitions data points into distinct groups (K clusters) based on specific and relative characteristics (Jain, 2010). It iteratively assigns each data point to one of K clusters. As a result, the centroids of K clusters are the best representations of a data distribution (or customer category). Understanding the patterns of consumer behaviour when purchasing products is pivotal for marketers because they can utilize this information to employ suitable strategies to maximize their profits. Choosing several clusters (K) is a key aspect of applying K-means clustering. There are several solutions to the obstacle of K-means clustering: (1) automatically assigning K, (2) preprocessing the data, and (3) obtaining multiple solutions and selecting the best solution based on criterion validators. The highlights of the key articles are summarized in **Table 1**.

Table 1. Studies on water ionizers, conjoint and k-means clustering.

Author(s)	**Methodology/Research areas'**	**Key findings**
Kulshreshtha et al. (2023)	Pricing Strategies	Consumers are highly price-sensitive, identifying features and segmentation using conjoint analysis and K-mean clustering.
LeBaron et al. (2022)	Health Benefits Perception	Consumers value health benefits such as improved hydration and antioxidant properties. Conjoint analysis quantified these preferences, and K-means clustering segmented consumers based on health benefit perceptions.
Vodounon et al. (2022)	Environmental Impact and Sustainability	Sustainable environmental features for clean and healthy water. Analysing features for reduced maintenance for environmental sustainability and consumer preference using Conjoint and K-means identifying eco-conscious consumer segments.
Wang & Wu (2014)	Optimal Product Features	Conjoint analysis to utilise core attributes and perceptions of optional attributes guiding product design and solutions to maximize overall customer satisfaction.
Singh & Gill (2013)	Brand Loyalty and Switching Behaviour	Conjoint analysis showed strong brand loyalty towards Enagic (Kangen). K-means clustering identified segments likely to switch brands based on price and features.
Green & Srinivasan (1978)	Consumer Preferences for Water Ionizers	Conjoint analysis revealed that consumers prioritize pH levels, price, and brand when choosing water ionizers.

4. Data Analysis

4.1 Data Collection

The Primary data on consumer preferences for water ionizers have collected using convenience sampling via a survey questionnaire. They were identified as prospective buyers of water ionizers through direct sales agents. The sample size for the data analysis was 479 participants. Survey tools, along with other methods, such as social media, email, and public group forums, have been used to access potential participants and collect participant responses for data analysis. The questionnaire consisted of closed questions that were structured to capture consumer preferences regarding the features of water ionizers. All data were treated confidentially and accessed for research only. Demographic information such as name, age, income, profession, and contact details was collected solely for research purposes in accordance with informed-consent guidelines.

Consumer characteristics were explored and enabled by demographics to consider the qualitative and subjective findings. Sex and age were considered categorical variables among the assessed variables (**Table 2**). However, using an interval scale to measure these variables provides better insights for research, with zero as the starting point. In terms of marriage, the dependent variable, almost 70% were currently married, implying that the remaining 30%, who were single, had approximately four times higher odds ratio of preferring water ionizers with a large-capacity characteristic than those of the married cluster. Data from 479 respondents were analysed in this study. Of the 479 respondents (**Table 2**), approximately 38% were female and 62% were male. As per the education levels of the respondents, an equal number of respondents (~11%) were high school graduates, the remaining 56% were either graduates/postgraduates or holders of a professional degree, and the rest did not disclose their qualifications. More than half (~64%) of the respondents earned INR 500,000 per month to INR 2,000,000, ~26% earned an annual income of less than INR 500,000, and only ~9% exceeded INR 2,000,000.

Table 2. Respondent demographics descriptive statistics.

Characteristics	**Category**	**No. of population**	**%**
Gender	Male	297	62.00
	Female	182	37.99
Age	Less than 18	77	16.08
	Between 18 to 30	134	27.97
	Between 31 to 45	153	31.94
	Between 46 to 60	86	17.95
	More than 60	29	6.05
Annual Income	Less Than 5 Lakh	127	26.51
	Between 5 to 10 Lakh	177	36.95
	Between 10 to 20 Lakh	130	27.13
	More than 20 Lakh	45	9.39
Education	High School	53	11.06
	Graduate	205	42.80
	Postgraduate	63	13.15
	Other	158	32.99
Household Size	Single	136	28.40
	Couple	112	23.38
	Family with Children	221	46.14
	Others	10	2.08

4.2 Conjoint Analysis

This study used a survey-based conjoint analysis in which respondents' ratings and rankings of alternatives were used to determine the attribute value. This research identified attributes and their levels to study the conjoint analysis, as mentioned in **Table 2**, and generated 16 cards for analysis of the ranking of consumer preferences using the SPSS tool, as mentioned in **Figure 4**. Received responses were collated and transformed using categorical data for the operation using Python code to obtain the utility score to validate the influence of attributes, as shown in **Table 3**.

Table 3. Attribute-level description.

Attributes	Level
Brand	Level 1: Enagic (Kangen) Level 2: Tyent Level 3: KYK
Type of pH Water	Level 1: 3 type of pH Water Level 2: 5 type of pH Water Level 3: 7 type of pH Water
Price (in INR)	Level 1: Less than 150K Level 2: Between 150 K to 250 K Level 3: More than 250 K
ORP (Oxidation-Reduction Potential)	Level 1: 0 to -200 mV Level 2: -200 mV and below
AMC (Annual Maintenance Changes)	Level 1: Less than 5K Level 2: Between 5K to 15K Level 3: More than 15K

Attribute levels have been chosen to reflect realistic configurations commonly provided by water-ionizer manufacturers in the Indian market. The pH and ORP categories align with the functional ranges typically promoted by leading brands, as noted in **Table 3**, thereby ensuring technical relevance and respondent familiarity. The brands included are well-recognized entities for perceived quality and market positioning. Price bands were determined to represent the typical segmentation of ionizers into entry-level, mid-range, and premium categories. The AMC categories reflect the routine service and filter-replacement costs typically incurred by consumers. Overall, the selected levels reflect prevailing market offerings, are easy for consumers to interpret, and are technically feasible within standard ionizer models.

The utility scores obtained in **Table 4** signify the importance and relevance of the attributes in choice-based conjoint analysis. Level 1 brand attributes were the most preferred, followed by Level 2, with Level 3 being the least preferred. The type of pH water (pH Type) preferred Level 2, while Levels 1 and 3 had negative utilities, indicating lower preference. The price attribute depicts Level 1 (likely the lowest price), whereas Level 3 (likely the highest price) is least preferred. For the ORP attribute, Level 1 was preferred over Level 2 and for the AMC attribute Level 2 was the most preferred, whereas Level 3 was the least preferred. **Table 5** further indicates the relative importance of the attributes.

In **Table 6**, the ANOVA test was used to compare groups to determine if there were significant differences among them and whether the variation between group means was greater than the variation within the groups. The p-value score < 0.05 for all attributes.

Table 4. Attributes utilities score.

Attributes	Utilities score
Brand	
Level 1: Enagic (Kangen) Level 2: Tyent Level 3: KYK	0.098530544 0.02158598 -0.120116524
Type of pH Water	
Level 1: 3 types of pH Water Level 2: 5 types of pH Water Level 3: 7 types of pH Water	-0.019197744 0.032679755 -0.013482011
Price (in INR)	
Level 1: Less than 150K Level 2: Between 150 K to 250 K Level 3: More than 250 K	0.090430106 -0.001064073 -0.089366033
ORP	
Level 1: 0 to -200 mV Level 2: -200 mV and below	0.03915126 -0.03915126
AMC (Annual Maintenance Charge)	
Level 1: Less than 5K Level 2: Between 5K to 15K Level 3: More than 15K	-0.03507506 0.134461291 -0.099386231

Table 5. Attribute-wise relative importance.

Attribute	Relative importance (%)
Brand	27.87
pH Type	30.35
Price	22.59
ORP	12.05
AMC	7.15

Table 6. Results for ANOVA test.

Attribute	Cluster mean square	Cluster DF	Error mean square	Error DF	F Value	P Value
Brand	350.2728	2	0.6459	7661	301.8393003	0.0000
pHType	1958.6750	2	0.2597	7661	5313.591694	0.0000
Price	391.9075	2	0.5803	7661	43.93696833	0.0000
ORP	302.5615	2	0.6445	7661	309.2466884	0.0000
AMC	1549.1817	2	0.3691	7661	3034.357291	0.0000

In **Figure 4**, card wise utility score based on 479 respondent's data has been obtained. These preferences highlight the importance of the ORP, Price, brand reputation, and versatility in pH options for consumers in the water ionizer market. The card-wise utility scores depict valuable perceptions of respondents' preferences for different product profiles, helping to understand the combinations of attributes that are most and least appealing. Businesses can use these insights to tailor their product offerings and marketing strategies to better meet consumer demand and enhance market penetration.

To gain further insight into the segmentation, we performed K-means clustering, a method of vector quantization (Celebi, 2011) that aims to partition observations into clusters in which each observation belongs to the cluster with the nearest mean. The goal is to group consumers based on their decision-making style when purchasing a water ionizer. The mean ratings assigned to each group were examined to determine significant differences. To form consumer clusters, the entries were considered as preference vectors for the chosen respondents. The identified consumer groups were profiled based on their attributes and corresponding importance.

Card	Brand	Types of pH Water	Price (in INR)	ORP	AMC (Annual Maintenance Charge)	Utilities Score
1	Tyent	3 Types of pH Water	Less than 150K	-200 and below	More than 15K	0.23
2	Enagic	3 Types of pH Water	Between 150K and 250K	0 to -200	Between 5K and 15K	0.34
3	KYK	7 Types of pH Water	More than 250K	0 to -200	More than 15K	0.23
4	Tyent	3 Types of pH Water	More than 250K	0 to -200	Between 5K and 15K	-0.17
5	KYK	3 Types of pH Water	Between 150K and 250K	0 to -200	Between 5K and 15K	-0.03
6	Enagic	7 Types of pH Water	More than 250K	0 to -200	Less than 5K	0.18
7	Tyent	3 Types of pH Water	Less than 150K	0 to -200	Between 5K and 15K	-0.12
8	KYK	5 Types of pH Water	Less than 150K	0 to -200	Less than 5K	-0.06
9	Enagic	7 Types of pH Water	Less than 150K	-200 and below	Between 5K and 15K	0.32
10	KYK	5 Types of pH Water	More than 250K	-200 and below	Between 5K and 15K	-0.06
11	Enagic	3 Types of pH Water	Less than 150K	0 to -200	Less than 5K	-0.08
12	KYK	3 Types of pH Water	Between 150K and 250K	-200 and below	Less than 5K	-0.22
13	KYK	7 Types of pH Water	Less than 150K	0 to -200	More than 15K	0.05
14	Tyent	3 Types of pH Water	Between 150K and 250K	0 to -200	Less than 5K	0.14
15	Enagic	7 Types of pH Water	Between 150K and 250K	-200 and below	More than 15K	-0.22
16	Tyent	7 Types of pH Water	Between 150K and 250K	0 to -200	More than 15K	-0.23

Figure 4. Card-wise utility scores.

4.3 Cluster Validation

Elbow Method: The elbow method was used to determine the optimal number of clusters by plotting the Within-Cluster Sum of Squares (WCSS) against increasing values of k. The point at which the WCSS begins to flatten - creating a visible ‘elbow’ indicates the most appropriate cluster solution for K-means. As shown in **Figure 5**, this inflection point guided the selection of the number of clusters for subsequent analysis (Ong et al., 2023).

Silhouette Plot: The Silhouette Score was used to assess the quality of the clustering solution by measuring both cohesion within clusters and separation between them (Naghizadeh & Metaxas, 2020). Higher values indicate better-defined clusters. As shown in **Figure 6**, the Silhouette analysis supported the four-cluster solution identified through the elbow method (**Figure 5**).

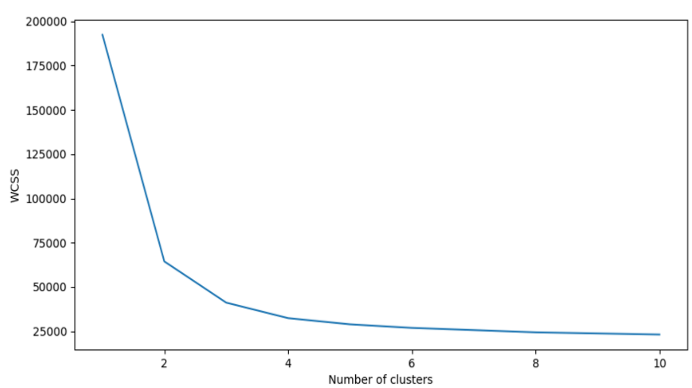

Figure 5. Optimal number of clusters using elbow plot.

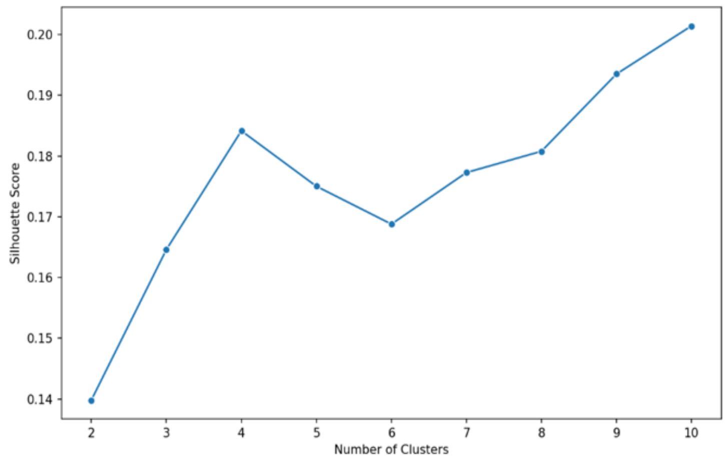

Figure 6. Silhouette scores for validating clusters.

4.4 Probability and Residual Plots

The probability plots in **Figure 7** (specifically the Q-Q plots) and the residual plot in **Figure 8** were used to assess whether the residuals from the regression model followed a normal distribution, which is vital for validating the statistical models. The points lie approximately along the reference line, which depicts the normal distribution using the Random Forest method, and the value of R is 0.987.

Figure 9, the pair plot shows the relationships between the features 'Price', 'ORP', and 'AMC' with clusters indicated by different colours. A pair plot is a powerful visualization tool that allows to explore the relationships between multiple variables in a dataset. It creates a matrix of scatter plots. This reveal trends, correlations, and potential outliers.

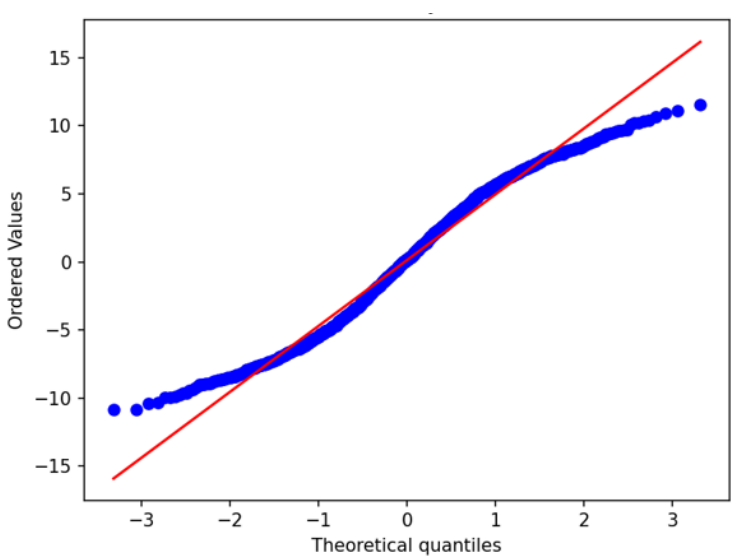

Figure 7. Probability plot.

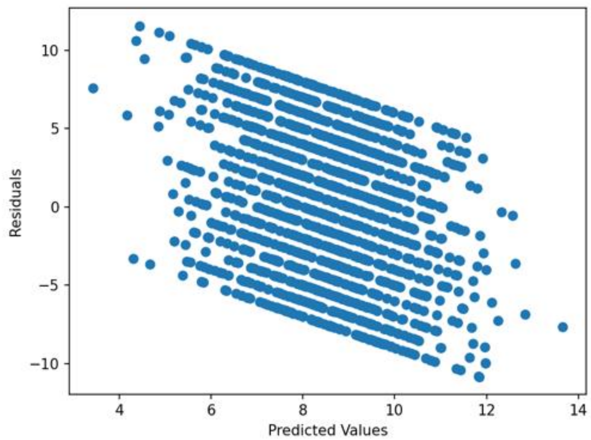

Figure 8. Residual plot.

Cluster formation using K-means clustering in **Figure 10** is shown for grouping similar data points based on their attributes and four clusters as evaluated and validated using the Elbow and Silhouette plot. It segments the respondent data into distinct groups to identify customer preferences in each cluster.

K-means clustering provides a clear segmentation of respondents, allowing for a deeper understanding of their preferences and behaviours. **Table 7** describes the number of respondents in each cluster and their percentage out of total 479 respondents. This information can be leveraged to make informed decisions on marketing, product development, and customer relationship management.

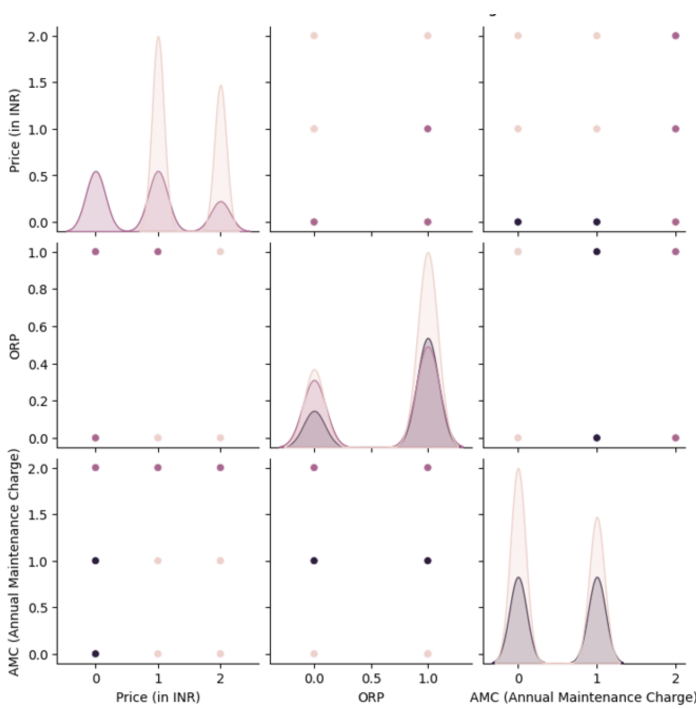

Figure 9. Pair plot for k-means clustering.

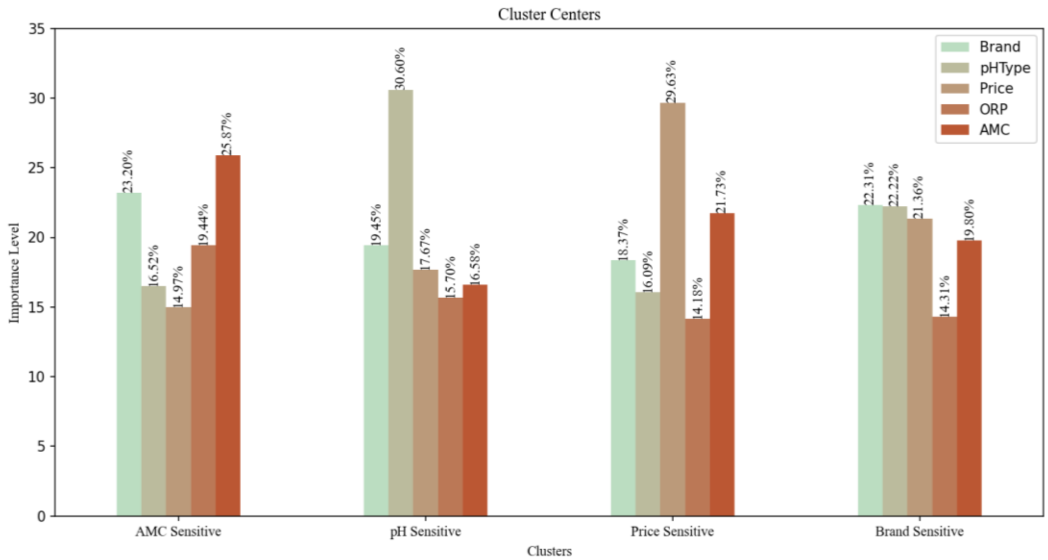

Figure 10. Cluster formation using K-mean clustering.

Table 7. Cluster-wise respondent.

Cluster	No. of respondents	% Respondents
AMC Sensitive	126	26.30
Brand Sensitive	116	24.37
Price Sensitive	122	25.47
pH Sensitive	113	23.86

5. Results and Interpretation

The results of the conjoint analysis show that pH is the most influential attribute, followed by brand, price, ORP, and AMC. The pH factor has attracted the most interest and is independent of the four remaining choice factors. Regarding the p-values, all p-values were extremely low, that is, less than the alpha of 0.05, and close to 0, and all attributes had high F values, indicating significant differences between the clusters for each attribute. This suggests that the clustering algorithm has effectively grouped the data points based on these attributes The permutation test of conjoint analysis identified five salient attributes that significantly affected consumer preferences for a water ionizer: brand, Type of pH Water (pH Type), ORP, AMC, and Price. This indicates the robustness of the findings of conventional conjoint analysis.

Based on the conjoint analysis, the ideal water ionizer for many consumers would have the following attributes, based on a maximum utility score of ~ 0.34.

a) Best Card: 2
b) Card Features:
- **Brand:** Enagic (Kangen)
- **Type of pH Water:** 3 types of pH water
- **Price**: Between 150K to 250K INR
- **ORP**: 0 to -200 mV
- **AMC:** Between 5K to 15K

Card 2 emerged as the optimal profile because it had the highest total utility score, calculated by summing the part-worth utilities of its attribute levels. In conjoint analysis, the profile with the highest combined utility corresponds to the rank with the highest predicted consumer preference.

Cluster analysis generated four segments. The unique characteristics of each segment are consistently supported by the demographic information and purchase decision behaviours. The obtained clusters are labelled based on their characteristics, which were supported by both demographic and choice-based model observations.

Cluster 1 (*AMC*): This segment consists of consumers who place strong emphasis on annual maintenance costs when evaluating water ionizers. These consumers are Maintenance Mavens and are more inclined towards sales and maintenance. This cluster involves 26% of respondents whose preference is for annual maintenance, and out of these 126 respondents, approximately 25% prefer this attribute.

Cluster 2 (*pH Sensitive*): The second cluster prominently derives Feature-Skeptics consumers who characterized the product features, which is more significant for water ionizers, consisting of ~24% of respondents, where more than 30% preferred the pH sensitivity of water ionizers and a water ionizer significantly improved the water quality.

Cluster 3 (*Price Sensitive*): This cluster defines the frugal consumer and contributes ~25% of the population, for whom price plays a significant role in the adoption of water ionizers. Approximately 30% of the respondents in this cluster consider price to play a significant role, and it has similar importance to the pH value in Cluster 2.

Cluster 4 (*Brand or pH equivalent*): This Cluster consists of ~24% of respondents and has a preference value of 22.31%, which is very close to 22.22% of the pH value percentage in the same cluster. The loyalist consumer preference in this cluster is slightly higher with respect to pH, which indicates that consumers in this cluster assign importance to brand and pH almost equivalently.

Holistically, the cluster analysis provided clear and actionable segments that help explain how different consumer groups evaluate water ionizers. These segments offer useful guidance for targeted marketing, product positioning, and future research on preference heterogeneity. The results show that attribute priorities, specifically pH level, brand, and price which vary meaningfully across groups, underscoring the value of combining conjoint analysis with clustering to reveal distinct decision-making patterns. Also, the dominance of pH and brand as key attributes suggests strong perceived benefits and subjective norms, consistent with HBM and TPB frameworks.

Evaluating and considering participants' demographics, younger and lower-income respondents tended to fall into the price- and pH-sensitive segments, whereas higher-income and older respondents were more represented in the brand-focused cluster. Married participants appeared more frequently in the AMC-sensitive group, reflecting their attention to ongoing household expenses. These demographic tendencies provide a clearer interpretation of the segment characteristics.

6. Discussion

6.1 Theoretical Implications

This study uses the idea of a behaviour model that combines the value of consumer behaviour attribute utilities to predict choice accompanied by widely adopted preferences. This study used consumer behaviour attributes and the results obtained were in line with the theoretical framework of marketing. This study confirms that the perception and behaviour of consumers when implementing purchase intention strategies in the dynamics of a competitive market must be based on consumer segmentation to sharpen the strategy alignment. By integrating behavioural theories with quantitative modelling, the study advances the theoretical discourse on health-tech adoption and consumer segmentation. It highlights the importance of aligning product attributes with consumer values. The empirical findings align closely with the theoretical expectations of HBM and TPB. The high importance assigned to pH type and ORP reflects strong perceived benefits, a core construct of HBM, indicating that consumers value attributes associated with health improvement and water quality. Likewise, the significance of brand corresponds to TPB's subjective norms, suggesting that consumers rely on trusted or socially endorsed brands when evaluating health-tech products. The prominence of price and AMC in several clusters' mirrors perceived barriers and perceived behavioural control, demonstrating that financial constraints shape adoption intention. Together, these patterns show that consumer preference structures in the conjoint model reflect the psychological drivers proposed by HBM and TPB.

6.2 Practical Implications

This study attempts to connect this discussion with real business implications. This study demonstrates the effectiveness of using analysis to identify consumer preference variability and segment consumer preferences in a membership market. This study can also be used as a reference for sellers, particularly for consumers who tend not to believe in certain products. Furthermore, from the seller's segmentation, the seller knows the type of consumer that commonly chooses these products. The seller only needs to provide announcements to those targeted to make a purchase. However, if a seller or producer incurs limited campaign costs, model segmentation may also be useful. Often, the seller asks questions about how to reduce scatter.

7. Managerial Implications

The findings offer practical guidance for water-ionizer marketers seeking to align products with consumer expectations. The conjoint and cluster results show clear differences in attribute preferences, enabling firms to design more relevant offerings and communicate value more effectively.

- *Product Development*: Focus on the attributes that most strongly influence consumer choice specifically pH options, brand reputation, and ORP performance. These insights can guide feature prioritization and help firms differentiate through meaningful product enhancements.
- *Pricing Strategy*: Use consumers demonstrated price sensitivity to set competitive yet value-driven pricing tiers. Utility scores from the conjoint analysis can support value-based pricing and help firms offer bundles or product variations aligned with customer willingness to pay.
- *Segment-Specific Marketing*: Leverage the four consumer segments identified through K-means clustering to tailor marketing messages. Highlight pH features for pH-sensitive buyers, reliability and brand heritage for brand-loyal consumers, affordability for price-sensitive groups, and long-term maintenance benefits for AMC-sensitive customers.
- *Targeting and Positioning*: Prioritize segments by size and profitability and position each product line to meet the specific needs of its most relevant cluster. Tailored promotions targeted digital campaigns, and segment-oriented positioning can enhance market reach.
- *Customer Experience and After-Sales Service*: Provide after-sales support, personalized usage guidance, and maintenance alerts to strengthen trust and long-term satisfaction—particularly for customers who value AMC considerations.

8. Conclusion, Limitations of the Study, and Future Work

This study explores consumer behaviour in the water ionizer market using conjoint and k-means cluster analysis. Health is regarded as a crucial factor in selecting a water source. Portable water purification systems such as water ionizer systems are valuable for enhancing the quality of drinking water from available sources. It is suggested that consumers become aware of the advantages of water ionizers in improving their health and well-being by using alkaline mineralized water. These findings suggest that consumer purchasing behaviour theoretically comprises brand, price, pH-water type, AMC, and ORP. This analysis supports the development and implementation of strategic marketing in the water ionizer industry. From a practical perspective, these findings are helpful for water ionizer-producing companies to ensure that marketing strategies are aligned with consumer behaviour, with the aim of ensuring organizational sustainability and profit. In terms of theoretical contributions, this study breaks new ground by demonstrating a new understanding of water ionizer technological trends and provides evidence for the concurrence of established product characteristics.

Future research could explore longitudinal consumer behaviour patterns to assess how preferences evolve over time, especially as awareness of water ionizers and their health benefits increases. Additionally, cross-cultural studies comparing consumer preferences in different regions or countries could provide insights into how cultural values and health perceptions influence product adoption. This would help validate the generalizability of the conjoint-cluster framework across diverse consumer markets.

Another promising avenue is the integration of digital analytics and behavioural tracking with conjoint-based segmentation. For instance, combining online browsing data or purchase histories with stated preferences could refine predictive models and enhance personalization strategies. Researchers could also investigate the role of influencer marketing, social proof, and digital trust in shaping consumer preferences for health-tech products. These directions would not only enrich the theoretical landscape but also offer practical tools for marketers navigating the evolving health-conscious consumer ecosystem.

This study had some limitations that should be addressed in future research. First, potential confounding variables were not included in this analysis. For example, purchasing location and the importance of product warranty could also be quantified using binary choice questions in future research. Second, consumer behaviour is liable to change; therefore, future studies could analyse the changing behaviour of consumers in relation to purchasing water ionizers. Future researchers could survey or use big data from consumers at an international level, which would provide greater certainty and accuracy for our understanding of consumer behaviour in the water ionizer market. A longitudinal study is suggested to examine the changes in the antecedents and consequences of consumer behaviour in the water ionizer market. In addition, the influence of new antecedents and consequences can be assessed in the high technology domain using new and improved techniques with technological advancements.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors wish to thank various anonymous reviewers for their valuable suggestions.

AI Disclosure

During the preparation of this work the author(s) used generative AI in order to improve the language of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Anand, A., Bansal, G., & Aggrawal, D. (2018). Choice based diffusion model for predicting sales of mobile phones using conjoint analysis. *The Journal of High Technology Management Research*, *29*(2), 216-226.

Axsen, J., & Kurani, K.S. (2012). Social influence, consumer behaviour, and low-carbon energy transitions. *Annual Review of Environment and Resources*, *37*(1), 311-340.

Backhaus, K., Wilken, R., & Hillig, T. (2007). Predicting purchase decisions with different conjoint analysis methods: a Monte Carlo simulation. *International Journal of Market Research*, *49*(3), 341-364.

Bruvold, W.H., Rosen, A.A., & Pangborn, R.M. (1975). Human perception and evaluation of water quality. *Critical Reviews in Environmental Science and Technology*, *5*(2), 153-231.

Celebi, M.E. (2011). Improving the performance of k-means for color quantization. *Image and Vision Computing*, *29*(4), 260-271.

Chater, N., Huck, S., & Inderst, R. (2010). Consumer decision-making in retail investment services: a behavioural economics perspective. *Report to the European Commission/SANCO*.

Dahl, D. (2013). Social influence and consumer behaviour. *Journal of Consumer Research*, *40*(2), iii-v.

Do Paco, A.F., Raposo, M.L.B., Filho, W.L. (2009). Identifying the green consumer: a segmentation study. *Journal of Targeting, Measurement and Analysis for Marketing*, *17*, 1, 17-25. https://doi.org/10.1057/jt.2008.28.

Facendola, R., Ottomano Palmisano, G., De Boni, A., Acciani, C., & Roma, R. (2023). Profiling citizens on perception of key factors of food security: An application of k-means cluster analysis. *Sustainability*, *15*(13), 9915.

Foxall, G. (2005). *Understanding consumer choice*. Springer. Dordrecht, The Netherlands.

Green, P.E., & Krieger, A.M. (1991). Segmenting markets with conjoint analysis. *Journal of Marketing*, *55*(4), 20-31.

Green, P.E., & Srinivasan, V. (1978). Conjoint analysis in consumer research: issues and outlook. *Journal of Consumer Research*, *5*(2), 103-123.

Grusec, J.E., & Davidov, M. (2010). Integrating different perspectives on socialization theory and research: a domain-specific approach. *Child Development*, *81*(3), 687-709.

Hausman, A. (2000). A multi-method investigation of consumer motivations in impulse buying behaviour. *Journal of Consumer Marketing*, *17*(5), 403-426.

Henry, M., & Chambron, J. (2013). Physico-chemical, biological and therapeutic characteristics of electrolyzed reduced alkaline water (ERAW). *Water*, *5*(4), 2094-2115.

Jain, A.K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters*, *31*(8), 651-666.

Johnson, M.D., & Selnes, F. (2004). Customer portfolio management: toward a dynamic theory of exchange relationships. *Journal of Marketing*, *68*(2), 1-17.

Josiassen, A., Assaf, A.G., & Karpen, I.O. (2011). Consumer ethnocentrism and willingness to buy: analyzing the role of three demographic consumer characteristics. *International Marketing Review*, *28*(6), 627-646.

Kan, M.P., & Fabrigar, L.R. (2020). Theory of planned behaviour. In Zeigler-Hill, V., & Shackelford, T.K., (eds) *Encyclopedia of Personality and Individual Differences* (pp. 5476–5483). Springer Cham, Switzerland.

Kodinariya, T.M., & Makwana, P.R. (2013). Review on determining number of Cluster in K-Means Clustering. *International Journal*, *1*(6), 90-95.

Kulshreshtha, K., Bajpai, N., Tripathi, V., & Sharma, G. (2019). Cause-related marketing: an exploration of new avenues through conjoint analysis. *Benchmarking: An International Journal*, *26*(6), 2017-2050.

Kulshreshtha, K., Sharma, G., & Bajpai, N. (2023). Conjoint analysis: the assumptions, applications, concerns, remedies and future research direction. *International Journal of Quality & Reliability Management*, *40*(2), 607-627.

LeBaron, T.W., Sharpe, R., & Ohno, K. (2022). Electrolyzed–reduced water: review I. molecular hydrogen is the exclusive agent responsible for the therapeutic effects. *International Journal of Molecular Sciences*, *23*(23), 14750. https://doi.org/10.3390/ijms232314750.

Lewin, J.E., & Donthu, N. (2005). The influence of purchase situation on buying center structure and involvement: a select meta-analysis of organizational buying behaviour research. *Journal of Business Research*, *58*(10), 1381-1390.

Lewis, R.C., Ding, S., & Geschke, U. (1991). Using trade-off analysis to measure consumer choices: the full profile method. *Hospitality Research Journal*, *15*(1), 75-92.

Louviere, J.J. (1994). Conjoint analysis. In Bagozzi, R. (ed) *Advanced methods of marketing research* (pp. 223-259). Wiley Blackwell. USA.

Mathras, D., Cohen, A.B., Mandel, N., & Mick, D.G. (2016). The effects of religion on consumer behaviour: a conceptual framework and research agenda. *Journal of Consumer Psychology*, *26*(2), 298-311.

Naghizadeh, A., & Metaxas, D.N. (2020). Condensed silhouette: an optimized filtering process for cluster selection in K-means. *Procedia Computer Science*, *176*, 205-214.

Nelson, R.R., & Consoli, D. (2010). An evolutionary theory of household consumption behaviour. *Journal of Evolutionary Economics*, *20*, 665-687.

Netzer, O., Toubia, O., Bradlow, E.T., Dahan, E., Evgeniou, T., Feinberg, F.M., Feit, E.M., Hui, S.K., Johnson, J., Liechty, J.C., Orlin, J.B., & Rao, V.R. (2008). Beyond conjoint analysis: advances in preference measurement. *Marketing Letters*, *19*, 337-354.

Ong, A.K.S., Prasetyo, Y.T., Esteller, A.J.D., Bruno, J.E., Lagorza, K.C.O., Oli, L.E.T., Chuenyindee, T., Thana, K., Persada, S.F., & Nadlifatin, R. (2023). Consumer preference analysis on the attributes of Samgyeopsal Korean cuisine and its market segmentation: integrating conjoint analysis and K-means clustering. *PloS one*, *18*(2), e0281948. https://doi.org/10.1371/journal.pone.0281948.

Pandey, S., & Aggrawal, D. (2024). Sustainable practices and acceptance of water ionizers: a structural equation modeling approach. *Management of Environmental Quality: An International Journal*, *35*(8), 1912-1928.

Pandey, S., & Aggrawal, D. (2025a). Modeling the enablers for sustainable adoption of water ionizers: an ISM-MICMAC approach. *International Journal of System Assurance Engineering and Management*, *16*, 868-882.

Pandey, S., & Aggrawal, D. (2025b). Studying kangen technology dissemination in Indian subcontinent: a mathematical modeling framework. *International Journal of Mathematical, Engineering and Management Sciences, 10*(4), 856-873.

Rao, V. R. (2014). *Applied conjoint analysis* (No. 2014). Springer, New York.

Roberts, J.A., & Pirog III, S.F. (2004). Personal goals and their role in consumer behaviour: the case of compulsive buying. *Journal of Marketing Theory and Practice*, *12*(3), 61-73.

Shirahata, S., Kabayama, S., Nakano, M., Miura, T., Kusumoto, K., Gotoh, M., Hayashi, H., Otsubo, K., Morisawa, S., & Katakura, Y. (1997). Electrolyzed–reduced water scavenges active oxygen species and protects DNA from oxidative damage. *Biochemical and Biophysical Research Communications*, *234*(1), 269-274.

Singh, S., & Gill, N.S. (2013). Analysis and study of K-means clustering algorithm. *International Journal of Engineering Research & Technology*, *2*(7), 2546-2551.

Suhartanto, D., Dean, D., & Farhani, I. (2024). E-grocery service loyalty: integrating food quality, e-grocery quality and relationship quality (young customers' experience with local food). *International Journal of Quality and Service Sciences*, *16*(1), 87-102.

Tseng, S.M., & Wu, P.H. (2014). The impact of customer knowledge and customer relationship management on service quality. *International Journal of Quality and Service Sciences*, *6*(1), 77-96.

Vodounon, H.S.T., Houédakor, K.Z., Amoussou, E., Tingbe, E.M.A., Nantob, M., Ayitchéhou, K.L., & Enoumodji, M. N.B. (2022). Contributing to the achievement of sustainable development goals: knowledge on water, sanitation and health risk in Cotonou and Lomé cities. *International Journal of Sustainable Development & World Ecology*, *29*(2), 164-175.

Wang, C.H., & Wu, C.W. (2014). Combining conjoint analysis with Kano model to optimize product varieties of smart phones: a VIKOR perspective. *Journal of Industrial and Production Engineering*, *31*(4), 177-186.

Yastica, T.V., Salma, S.A., Caesaron, D., Safrudin, Y.N., & Pramadya, A.R. (2020). Application of theory planned behaviour (TPB) and health belief model (HBM) in COVID-19 prevention: a literature review. In *2020 6th International Conference on Interactive Digital Media* (pp. 1-4). IEEE. Bandung, Indonesia.

Zhang, M., Luo, M., Nie, R., & Zhang, Y. (2017). Technical attributes, health attribute, consumer attributes and their roles in adoption intention of healthcare wearable technology. *International Journal of Medical Informatics*, *108*, 97-109.