Vol 3 No 1 (2023)
Journal of Philanthropy and Marketing
E-ISSN: 2691-1361

ORGANIC OPTIONS: A STUDY OF HYDERABAD, TELANGANA CONSUMER OPINIONS USING SENTIMENTAL ANALYSIS

Dr. Ravi Prakash Kodumagulla
Professor, School Of Management, Presidency University, Bangalore, India
ORCID:0000-0002-9764-6048

Abstract
This research investigates consumer opinions on organic options in the city of Hyderabad, Telangana, employing sentiment analysis as a methodology. With the growing awareness of health and environmental concerns, the demand for organic products has witnessed a surge in recent years. Understanding consumer sentiments towards organic options is crucial for businesses and policymakers to align their strategies with consumer preferences. The study utilizes sentiment analysis techniques to analyze a diverse set of opinions sourced from social media platforms, reviews, and online forums. By employing natural language processing algorithms, the sentiments expressed by consumers are categorized into positive, negative, or neutral. The research aims to discern patterns and trends in consumer sentiments, shedding light on the factors influencing their perceptions of organic options. The goal of this study is to collect all of the organic food-related tweets and analyze the sentiment behind them. This study offers suggestions for more objective research methods in studies of food consumption and answers to a desire for the use of big data and text mining in several research domains. Since the food industry is one of the leading causes of climate change, understanding how this influences customer tastes is becoming more and more important. There are a lot of problems with using self-reported methodologies like surveys and interviews to look at how people see organic food.So, to look at how people generally feel about organic foods, we used more objective approaches like text mining and big data in our study. We gathered 43,724 tweets by using Twitter's streaming API. Our topic modeling strategy was based on Latent Dirichlet Allocation (LDA). To find out how well they were selected, we checked whether the topics were relevant. Syuzhet gauged popular sentiment by using the NRC emotion lexicon. Discussions on organic plant-based diets, environmental preservation, organic farming and standards, authenticity, home-delivered meals, and related subjects were indicated by the topic modeling results. The sentiment analysis results show that organic foods are generally well-received by Hyderabadi customers, while some of them are sceptical about the health benefits and pesticide-free promises made for them. The study adds to the body of knowledge on consumer behavior by using research methods based on big data and text mining. By providing a fresh viewpoint on public sentiment toward organic food, this study contributes to the existing body of literature and research on sustainable food consumption.
Furthermore, the study explores the implications of these sentiments on the organic market in Hyderabad, providing valuable insights for businesses and policymakers. The findings of this research contribute to the existing body of knowledge on consumer behavior towards organic products, facilitating informed decision-making in the organic sector. The use of sentiment analysis

ensures a nuanced understanding of consumer opinions, allowing for a comprehensive evaluation of the organic landscape in Hyderabad, Telangana.

Keywords: Organic foods, Text mining, Big data, Sentiment analysis, Latent Dirichlet Allocation (LDA)

Introduction

The most common approach to study customer behavior, including food-related beliefs and emotions, uses the self-reported method, e.g., participants declare themselves their feelings and emotions in interviews or verbal questionnaires [1, 2]. It stands for significant limitation of such studies. While self-report methods have many advantages, they might be affected by biases such as social desirability bias, response bias, and com- mon method bias [3, 4]. Moreover, some problems are very hard to capture; for example, emotions are, by nature, subjectively experienced in a specific context, so their objective assessment is very difficult [5, 6]. Wang et al. [7] and Feizollah et al. [8] argue that state- of-art computational techniques based on machine learning methods can potentially eliminate such methodological issues.There is growing interest in understanding consumer choices for foods [9, 10]. It is motivated, first of all, by climate change a serious global issue that poses an urgent and perhaps one of the greatest challenges facing humankind [11, 12]; the food industry contributes predominantly to these effects. Agriculture accounts for over a quarter of global greenhouse gas emissions; half of the total habitable land is used for agriculture; it uses 70% of global freshwater withdrawals and causes 78% of waterways' pollution; 94% of mammal biomass (excluding humans) is livestock [13, 14]. Unsustainable food con- sumption and its tangible consequences on human health and the environment, direct the public attention to organic foods which are viewed as ecological and healthy [9, 10]. European Union (EU) describes organic production as an overall system of farm man- agement and food production that combines best environmental practices, a high level of biodiversity, the preservation of natural resources and the application of high animal welfare standards [15].

The objective of this study is to identify the topics that users post on Twitter about organic foods and to analyze the emotion-based sentiment of those tweets. People find social media platforms convenient to share their experiences, attitude, and opinion. The rise in the number of active users and users' contents on Twitter delivers the scope for scientific exploration of public attitudes. In the present study, we extract the latent top- ics on organic foods from Twitter data and analyze the public sentiments about such foods. The study is the first of its kind, in this line of research, to use text mining based on unsupervised machine learning technique, which eliminates the limitations of sample size and subjectivity of conventional methods.So far, the studies on food consumption have utilized rather subjective traditional research methods, such as questionnaire surveys and interviews [16–19]. Although the body of research on organic food consumption is quite large, the question of why peo- ple buy organic food is still not fully understood [16, 20, 21].

Literature review

Vol 3 No 1 (2023)
E-ISSN: 2691-1361

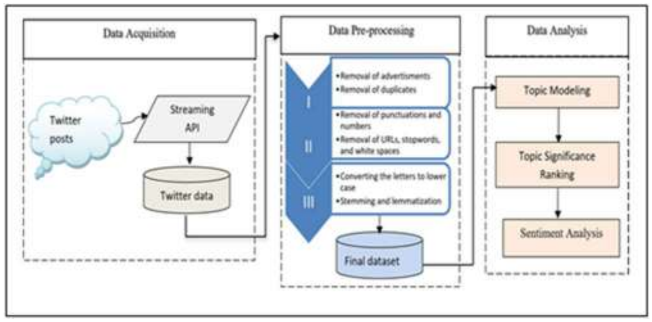
Organic food production is based on environmentally sustainable techniques excluding chemical or synthetic additives; its ecological nature strongly supports ecosystems and bio-diversity. Organic food production and consumption are also considered as animal-friendly and related to fairness and human health. Recent years have brought increased consumers' interest in organic food. Its global market is valued at 96.7 billion USD and a growing number of countries adopts distinct regulations for its culti- vation . Organic food production and trading are among the fastest-growing indus- tries in the food market in Europe, South America, Oceania, and Japan .

Customers buy organic foods due to rising food safety concerns [17] and health con- sciousness [18], but also because of its taste. Consumer motivations for choosing organic foods are categorized as related to health, environment, and social conscious- ness [16]. Dr.Naveen Prasadula A rising level of concern for environmental and ecological welfare supports organic food consumption as animal friendly [20] and as a counter-option to conven- tional food production using chemical, synthetic and genetically modified means [24,]. Other non-egotistical factors of organic food consumption include supporting local producers and reflect concern for society and consumer social surroundings [19]. Recent studies suggest that perceived values (utilitarian and hedonic) influence con- sumer willingness to buy organic foods. It is the perceived value of a product from the multisensory and emotive aspects. The utilitarian value is the assessment of functional benefits and drawbacks of a product or service. In the context of organic foods, the utilitarian value refers to the nutritional quality, purity, safety, and healthy attributes . The hedonic value of organic food refers to the pleasure felt from the taste and the freshness and purity.

Concerning emotions influencing sustainable customer behavior, the picture is also very complex. Literature delivers evidence for the consequences of both negative and positive emotions in this regard. Among negative emotions, e.g., guilt is argued to influence sustainable behaviors because of consumer feelings of moral responsibility for the environment. Also, sadness was shown to affect more pro-environmental behaviors, such as giving higher monetary donations to sustainable causes. On the other hand, consumers are likely to engage in sustainable behaviors when they derive positive emotions from the behavior. For example, joy and pride influence intentions to decrease plastic water bottle usage, while optimism can motivate to main- tain such behaviors over time.

Research method

This section introduces the methods used in the study, followed by the subsections out- lining each stage in detail. Figure 1 depicts the methodological architecture of the study. As shown in Fig. 1, the first step involved data acquisition. Tweets are collected via Twit- ter APIs using the keyword. In the second step, the tasks of data preprocessing were performed (please refer to the Data collection and Pre-processing sections for more details). In the third step, the final data obtained from the second step was analyzed. Topic modeling was applied for topic extraction followed by topic significance ranking. In the last step, emotion-based sentiment analysis was performed, wherein the underly- ing emotions in the tweets were calculated and visualized the overall results.



Data collection

Twitter posts were extracted for this study. Twitter is a very popular online social net- work for mass communication and information dissemination and referred to as the gold mine of data. People find Social Networking Sites (SNS) a platform to share their views, opinions, information, and ideas at any time, thereby leaving the scopes for scientific research. The data is easily accessible and is useful for those studying public attitudes, opinions, beliefs, and behaviors. In this study, tweets were obtained by using Twitter Streaming Application Programming Interface (API). R 4.0.4 and Python
3.9 were used for the data extraction, storage, pre-processing, data mining, and result visualization. Tweepy, a popular Python library, was used for accessing the Twitter API. The tweets were streamed for the keyword ‘’Organic Food’’. Only tweets written in Eng- lish were considered, with no geographical restriction. The extracted dataset has the Tweet object which includes fundamental attributes such as ‘created_at’ (the time when this tweet was created), and ‘text’ (tweets), screen_name, and geo-tagged location. How- ever, we have taken only tweets in our analysis.

Data pre-processing

Social media data is interesting but is unstructured. A piece of meaningful informa- tion can be drawn if the quality data is ensured. The unstructured and semi-structured data need pruning to get an insight from it. The quality of Twitter data in this study was ascertained through the framework of accuracy proposed by, followed by extensive data pre-processing and cleaning. The accuracy was ascertained keeping in mind the query error, interpretation error, and coverage error during the data collection phase as suggest.We used Microsoft Excel and R Programming Language for data pre-processing. We adopted the following three steps for data pre-processing. Denoising of data was done in the first step. In here, advertisements, duplicate data, and irrelevant posts were deleted. In the second step, stop words, URLs, symbols, and the words that appear frequently and do not contribute to sentiment analysis were also removed. We employed the ‘tm’ package to remove such contents from the text data. Stop words, such as is, the, an, how, and what, were eliminated as these words do not contain relevant information. Similarly, URLs and numbers also do not contain any information, thus were eliminated. Finally, in step 3, words were converted into the lower case before stemming and lemma- tization was done. Thus, the cleaned data obtained was considered in the final analyses of the study.

Topic modeling

Latent semantic analysis (LSA), probabilistic latent semantic analysis (pLSA), and LDA are the three most commonly used topic modeling techniques. We adopted LDA in this study for the following reasons. LSA is an effective dimensionality reduc- tion technique, which can achieve significant compression in large collections while capturing some aspects of basic linguistic notion. However, the drawback of LSA is its inability of fitting a model to data to represent the documents into multiple topics. Although the pLSA approach solves the representation challenge in LSA, it cannotgeneralize to unseen documents due to the lack of a well-defined generative model. The method is also prone to overfitting, which is a serious issue, whereas LDA is capable of performing dimensionality reduction, semantic annotation, mixture modeling, and generalization ability without such major issues. Since this study is based on the cross-sectional research design, analysis of the temporal pattern of associated topics and topic correlation is out of the scope of this paper. Therefore, the topic modeling techniques like 'Topics over Time', 'Dynamic Topic Model' and 'Pachinko Allocation Model' are ruled out. Thus, LDA-based topic modeling suits well for achieving the objectives of this study.LDA is a sophisticated unsupervised machine learning technique for identifying the key topics from large textual data. It has been widely used in the field of natu- ral language processing (NLP) among several topic modeling algorithms [7]. It is a three-stage Bayesian probabilistic model. The model gives the topic of each docu- ment in the documents (D) with a distribution over the topics (K), and each topic is a multinomial distribution over words (W) in the corpus. The statistical model adopts the following three stages generative process (Fig. 2) for a corpus D of M documents with length Ni of each; α is the Dirichlet parameter of per-document topic distribu- tions, and β is the Dirichlet parameter of per-topic word distribution. And, θi and φk denote the topic distribution for the document i and the word distribution for topic k, respectively.

Based on the definition, LDA assumes the following generative processes for each tweet (w) in a corpus (D):

1. Cfloose N ~ Poisson (ξ), wflere N denotes tfle lengtfl of documents;
2. Draw a topic distribution, cfloose θd ~ Dir(α), wflere α is tfle parameter of tfle Dir- icfllet prior on tfle per-tweet topic distributions; and
3. For eacfl of N words wn:

(a) Cfloose a topic zn ~ Multinomial (θ); and

(b) Cfloose a word wn from p(wn|zn, β), a multinomial probability conditioned on tfle topic zn.

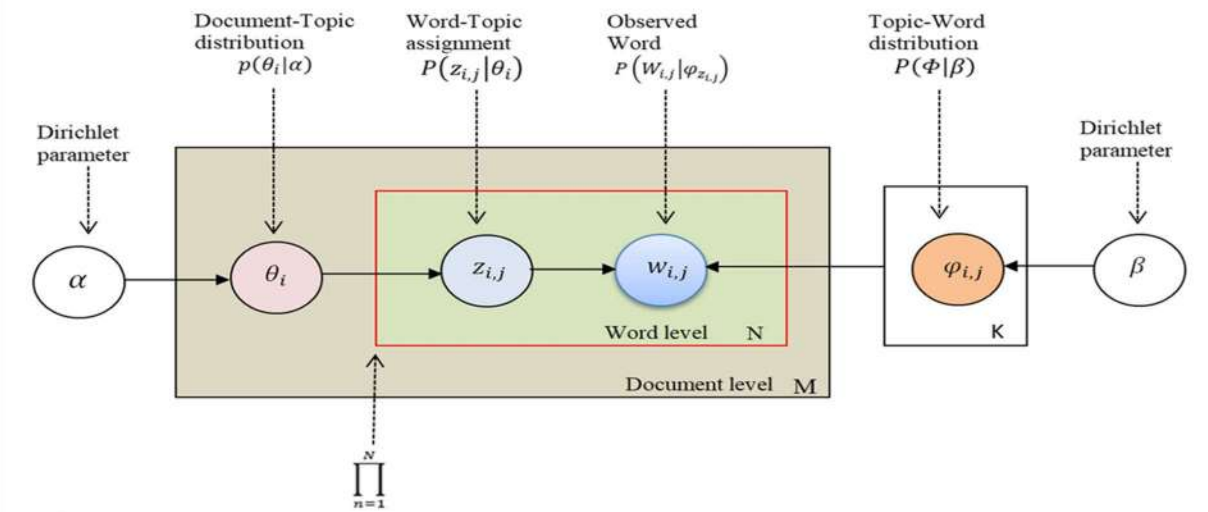


Fig. 2 Graphical model representation of LDA

Sentiment analysis

Sentiment analysis (also known as opinion mining or emotion AI) is located at the heart of NLP, text mining, and computational linguistics. It measures the subjective information extracted from textual data. In this era of the internet and social media, sen- timent analysis has gained much popularity among researchers from different domains for its applicability in a wide range of fields such as psychology, linguistics, public health, and business management. In the current study, the word-level sentiment analysis was performed. NRC Emotion Lexicon was used to list the words and their association with eight basic emotions (trust, fear, surprise, sadness, disgust, anger, anticipation, and joy) and two sentiments (negative and positive). Syuzhet package was utilized to analyze the underlying sentiments. The algorithm calculates the presence of eight different emo- tions and sentiments in the text dataset. It assigns each token (i.e., word) in the corpus a score corresponding to each emotion and sentiments; '1' if it is associated, otherwise '0'. Thus, a data frame containing sentiment scores is obtained, where each row represents a word and columns represent eight different emotions and two sentiments.

Results

The data for this study was collected from Twitter. The tweets posted between January 10, 2021 and March 7, 2021 was extracted using Python. A total of 43,724 tweets were collected. However, after removing the duplicates, 41,009 tweets are processed for fur- ther analysis. Before the topic analysis, it is necessary to evaluate the models.

Topic models' evaluations

LDA topic modeling is based on probabilistic inference; hence, requires a huge amount of data and tuning to get reasonable results. We used two measures- perplexity and topic coherence- to evaluate the best underlying topics in the corpus. Perplexity is defined as the inverse probability of the test set, normalized by the number of words. It is an intrinsic evaluation metric and is measured as the normalized log-likelihood of a test set data. It is a general quality measure for the entire model, and captures how well a probability model predicts the sample for new data it has not seen before.

For training and validation of the model, the data was divided into two sets. 80% of data (in-sample set) was employed to train the LDA model and the remaining held-out set (validation set) of 20% data was employed for model validation. Table 1 shows the results of perplexity scores of 15 topics. The model with nine topics scores the minimal validation perplexity of 237.5, indicating that the model with eight topics is more reli- able than the other models. The perplexity validation does not test the semantic simi- larity between words in a topic. Therefore, perplexity optimization cannot yield human

Table 1 Validation perplexities under the different numbers of topics

Number of topics	Validation perplexity	Number of topics	Validation perplexity	Number of topics	Validation perplexity
1	290.5	6	247.9	11	244.2
2	269.1	7	241.1	12	256.9
3	276.4	8	237.5	13	251.9
4	253.7	9	239.4	14	270.7
5	245.6	10	243.3	15	267.2

interpretable topics. Thus, this test alone may not be an adequate measure for pre- dicting the best model. This limitation of perplexity warrants a test for topic coherence.

Coherence is another method of evaluation of a topic model. It measures the degree of semantic similarity between high scoring words in the topic. The coherence score is calculated based on pairwise scores of the top n-frequently occurring words in a topic. There are different coherence measures discussed in the literature. However, we used the CV measure, the best measure to compare different topic models based on their human interpretability. The measurement helps to distinguish between topics that are an artifact of statistical inferences, and semantically interpretable. Figure 3 shows the coherence score for the different number of topics. A model with the highest coher- ence score before flattening out or a major drop is considered as the best model. To our surprise, both the tests confirm the presence of eight topics in our data. Therefore, we picked a model with eight topics (k = 8).

LDA model

Based on the results of perplexity and coherence scores, we ran an LDA model of 8 top- ics with 12 terms. Topics are labeled based on the identification of a logical connection between most the frequent terms of the topic. Table 2 presents the topic labels with their key terms. Topic 1 and Topic 2 are about the United States (US) politics as tweets were collected between January 10 and March 7, 2021, which is very close to an incidence in the US. Jacob Chansley, a Capitol Hill attacker, demands all-organic foods inside the prison. This incident has led to a huge inflow of Twitter posts related to US politics and organic foods. Topic 3 discusses organic food in connection with food additives such as pesticides and chemicals. The topic is composed of both positive perceptions (i.e., organic food has no additives) and negative or skeptical views (i.e., organic food is not free

Vol 3 No 1 (2023)
E-ISSN: 2691-1361

from additives). It can be understood with the tweets: Deceptive Labels on Food. Making sure you understand the terms that are used, what if they are not using

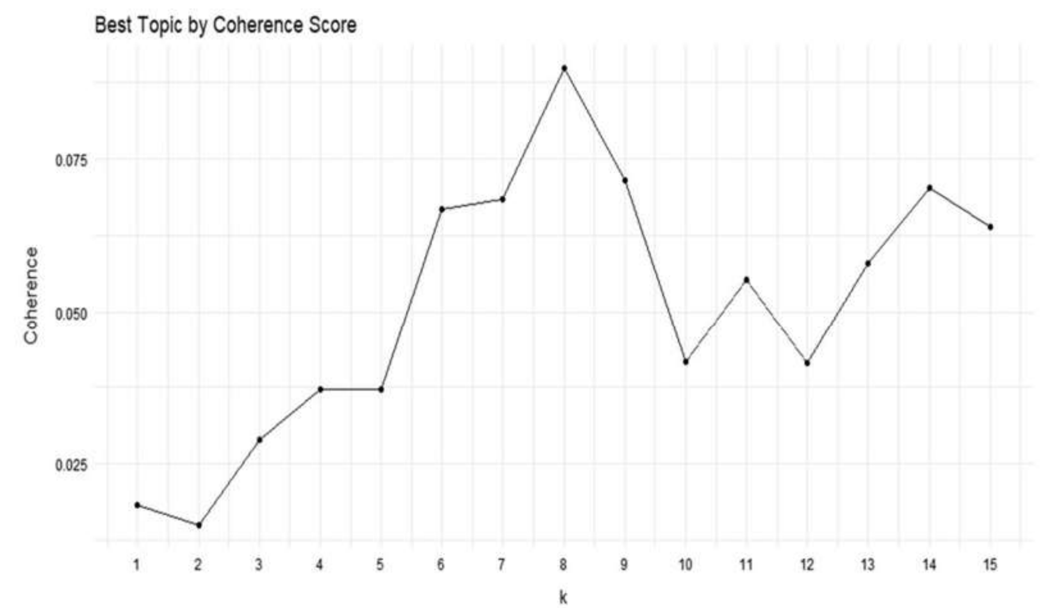


Fig. 3 Best topic by coherence score

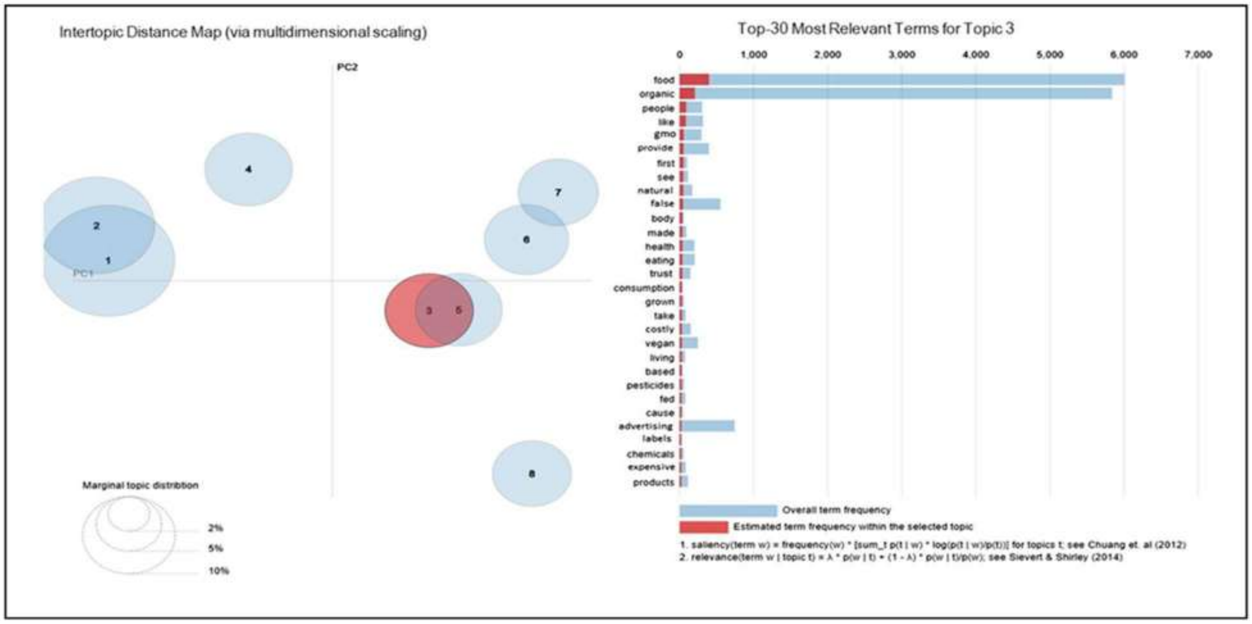
Table 2 Topics listing top 12 key terms extracted from LDA model

Topic id	Terms	Label
Topic 1	food, organic, jail, judge, Capitol, horns, get, hunger, riot, ordered, fur, strike	US politics (Attack on Capitol Hill)
Topic 2	organic, food, get, jail, man, white, prison, guy, judge, horns, privilege, vacation	US politics (Capitol attacker's demand for organic food)
Topic 3	organic, food, people, consumption, health, vegan, grown, eat-ing, fed, pesticides, chemicals	Authenticity
Topic 4	food, organic, month, seasonal, three, spring, package, survival,vitality, bundle, chakra, better	Seasonality
Topic 5	organic, food, plant-based, vegan, diet, ecological, refreshing, vegetables, health, future, good	Plant-based diet
Topic 6	organic, food, plant, local, fresh, natural, farming, agriculture, save, planet, impact, world	Saving the planet
Topic 7	farming, choose, harvest, latest, technology, crops, labels, stand-ards, agriculture, supply-chain, organic, focus	Organic farming and standardization
Topic 8	online, grocery, demand, local, store, orders, delivery, affordable, save, COVID19, planet, markets	Food delivery

US politics (Attack on Capitol Hill)

US politics (Capitol attacker's demand for organic food)

Authenticity Seasonality Plant-based diet Saving the planet Organic farming and standardization Food delivery



organic eggs feeding the chickens GMO FOOD. The key terms are people, health, grown, eating, chemicals, etc. Topic 4 is about the seasonality of organic foods. It emphasizes on benefits of choosing seasonal organic foods. The key terms are seasonal, package, vitality, and better.

Topic 5 discusses the importance of shifting toward plant-based foods. Some of the key terms are plant-based, vegan, diet, and vegetables. Topic 6 is about sav- ing the planet by natural and local farming which is suggested by terms such as nat- ural, planet, save, impact and world. Topic 7 highlights the need for technology and standardization in organic farming and supply-chain. The key terms are farming, organic, technology, and standards, etc. The last topic discusses the surge in online orders of organic foods and delivery systems, presumably caused by the COVID-19 pandemic.The visual display map of topic models produced using LDAvis highlights the topic with its top 30 most relevant terms. The display map of Topic 3 is shown below as Fig. 4, and the visual display map of the remaining five topics on organic foods is appended at the end of the paper. The visualization provides the global view of topics with the terms highly associated with the individual topic.In the visual display map on the left side, the distance between the circles indicates the topic similarity (or dissimilarity), i.e., the closer the circles, the more similar the themes. And, the size of the circle depicts its prevalence. The horizontal bar chart on the right side of the visualization depicts the terms most relevant to the selected topic.As per the display map (Fig. 4), Topic 1 and Topic 2 are similar to each other but dif- fers much from other topics. Similarly, Topic 3 and Topic 5 are close to each other. Topic 8 is away from other topics and refers the unrelatedness as it discusses organic food demands and online deliveries during the COVID-19 pandemic.

Topic significance ranking

We assessed topic quality through topic significance ranking (TSR) scores based on the criteria proposed by TSR is a novel unsupervised analysis of Probabilistic Topic Models (PTM). We applied a 4-phase Weighted Combination decision strategy to evalu- ate the inferred topics of PTM to evaluate their semantic significance. Topic significance is obtained by combining the information from the multi-criteria measures to form a single index of evaluation based on a Weighted Linear Combination (WLC) decision strategy. WLC is a widely used technique in the area of multi-criteria decision analysis. WLC assesses each topic by the following formula:
where Nm is number of different measures, Wm refers the weight of the measure in the total score, and Sm,k is the score of k th topic for the th measure.A 4-phase weighted combination approach was implemented. Sm,k and Wm scores were to be computed on different scales and criteria; therefore, measures are standardized before combination.

Phase 1: Standardization procedure

In the first phase, standardization procedures are performed to transfer each distance measure from its true value into two standardized scores (relative score of the distances and weight value).To compute both the scores Sm,k and weights Wm, two standardized procedures are used for each of the criteria. The first, score is re-scaled based on the weight of each score against the total score overall topics and is expressed in Eq. A significance ranking algorithm was applied on the topics discovered by LDA with K set to 8. This technique has the potential to properly rank the topic based on its true significance. The rank of a topic depends on its distribution of background words. A topic with higher TSR describes the underlining themes better and presents the

Table 3 Topic significance rank

Topic id	Topic label	$\hat{S}$	$\hat{W}$	TSR	Rank
Topic 5	Plant-based diet	21.3	0.8	17.0	1
Topic 3	Authenticity	20.7	0.8	16.6	2
Topic 4	Seasonality	19.8	0.8	15.8	3
Topic 7	Organic farming and standardization	18.5	0.8	14.8	4
Topic 6	Saving the planet	16.3	0.8	13.0	5
Topic 2	US politics (Capitol attacker's demand for organic food)	15.7	0.8	12.6	6
Topic 8	Food delivery	14.8	0.7	10.4	7
Topic 1	US politics (Attack on Capitol Hill)	14.5	0.7	10.2	8

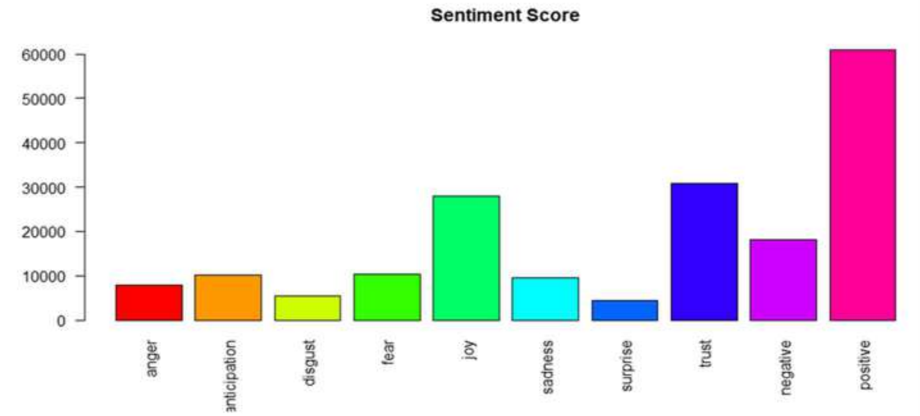


Fig. 5 Public sentiments toward organic foods

meaningful class semantics. Table 3 presents the topic significance rank index. The top- ics are ordered by their rank.According to our LDAvis results, Topic 1 and Topic 2 are the most prevalent topics. However, these two topics receive low significance ranks. Topic 5 (Plant-based diet), Topic 3 (Authenticity), and Topic 4 (Seasonality) are the three most significant topics.

Sentiment results

NRC lexicon enabled us to classify eight different emotions in addition to positive and negative sentiments. The negative emotions include fear, anger, disgust, and sad- ness, while positive emotions include joy, trust, anticipation, and surprise. The results of sentiment analysis show that public views toward organic foods are mostly positive (see Fig. 5). The results also show the presence of negative emotions but in a lower pro- portion as compared to positive ones. The frequent positive words for organic food are healthy, safe, fascinating'', eat, perfect, vitality, aroma, and delicious, etc. Joy and trust are two prominent emotions expressing positive emotions about organic foods with a total sentiment score of more than 30,000 for each.

The frequent negative words are unnatural'', waste, doubt, junk, ridiculous, fake, and unbelievable, etc. The keywords suggest that people are suspicious about the authenticity of organic foods, and express negative emotions. Some of the tweets are: Only 4–6% of the food is organic. The rest is produced by a few major food processors and full of chemicals, Can I sue the food place for false advertising? and All food is organic. Inorganic matter can't be digested. Therefore, the fact cannot be ignored that not every- one is convinced about organic claims, i.e., people are still skeptical about organic foods available in the markets being natural, healthy, and chemical or pesticide-free. However, the entire negative emotions in the results are not caused by the public distrust alone. It contains the negative emotions about the US riot and politics over organic foods (insur- rection, disgraceful, riot, attack, etc.).

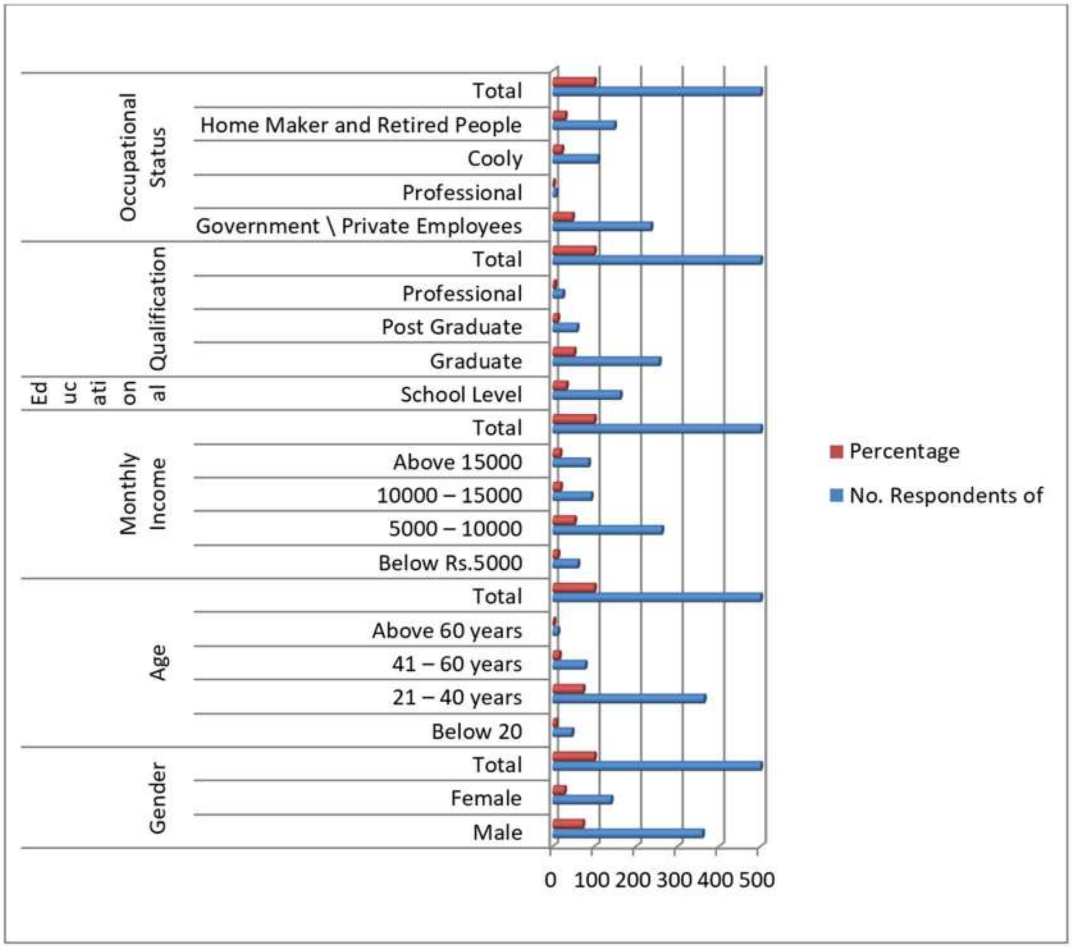
The survey was conducted to examine customer attitudes on purchasing organic food. Goals of the study are taken into consideration while the data are categorised and examined. Analysis has been done using statistical tools like percentage, correlation, and multiple regression.

COMPUTATIONAL AND INFERENTIAL ANALYSIS OF DATA

RESPONSIVES' DEMOGRAPHICAL PROFILE

Vol 3 No 1 (2023)
E-ISSN: 2691-1361

The Respondents' Demographics, as Shown in Table 1



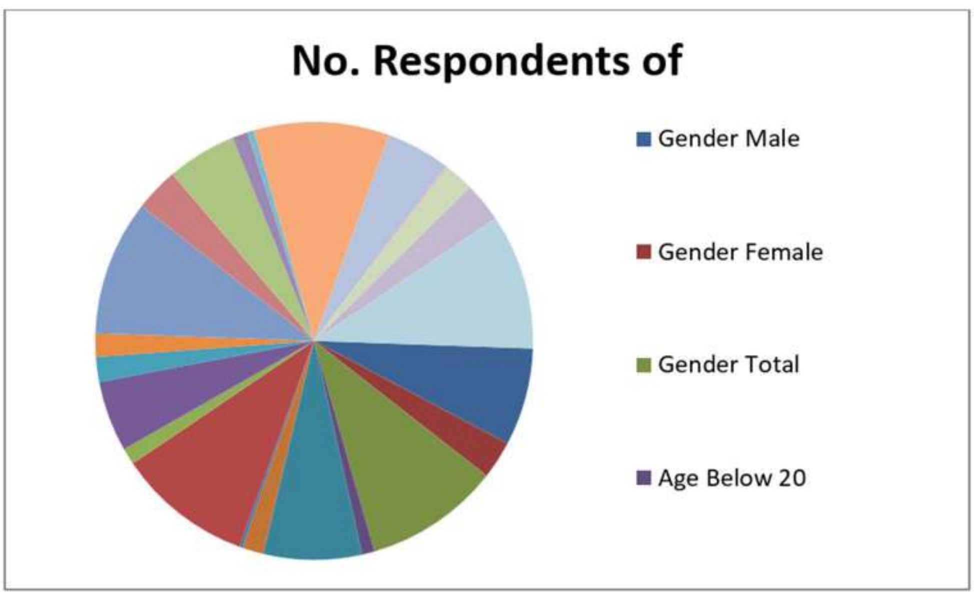
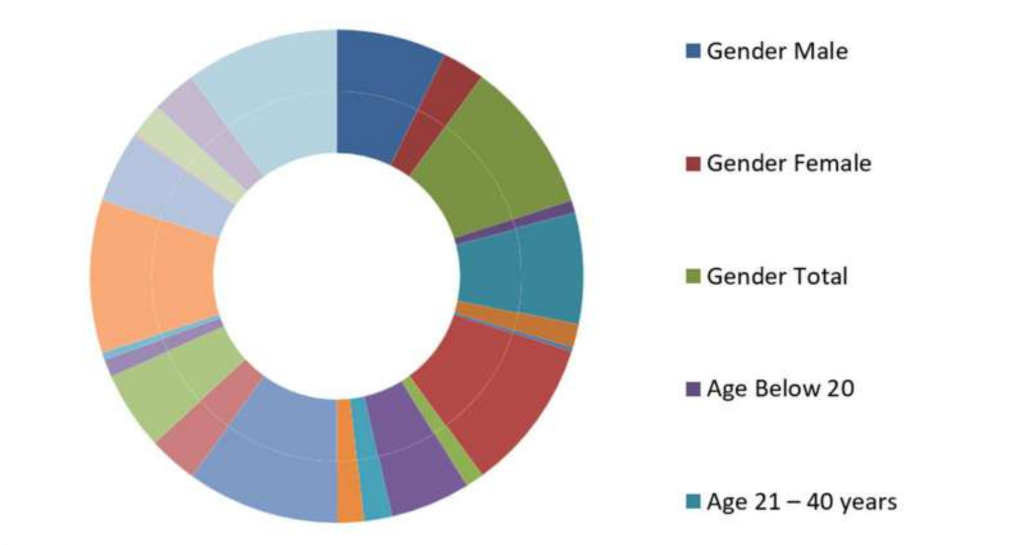


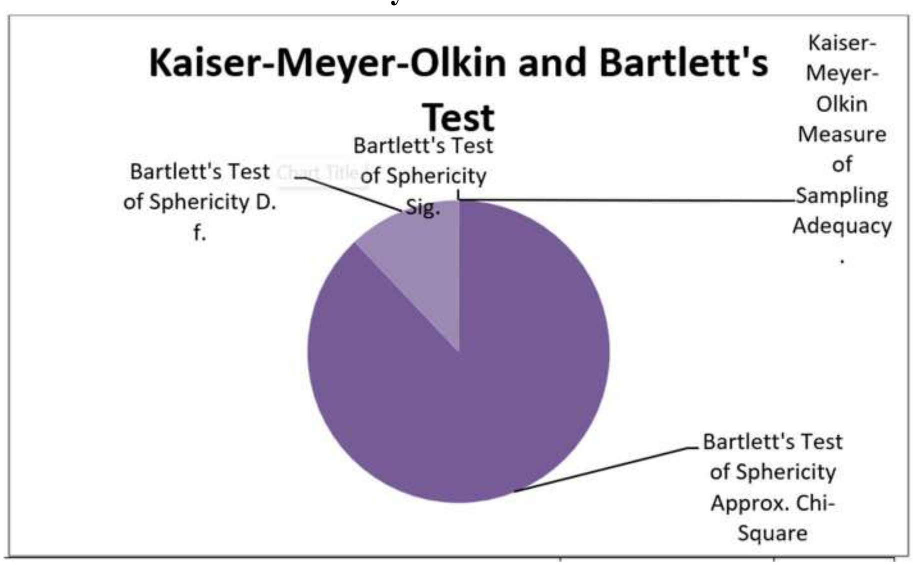
Table 1 shows that, compared to female respondents (28.0%), men (72.0%) made up the majority of respondents in the sample data. The majority of respondents (72.8%) belonged to the age range of 21 to 40, while the least amount (2.4%) of respondents were over 60.



PERCEPTIONS TOWARDS THE PURCHASE OF ORGANIC FOOD

Market demand has a big impact on whether organic production and processing will be adopted. As a result, attitudes and perceptions of consumers toward organic food products are reflected in this. Factor analysis has been used to examine consumer perceptions of buying organic food.

Table 2 Kaiser-Meyer-Olkin and Bartlett's Test



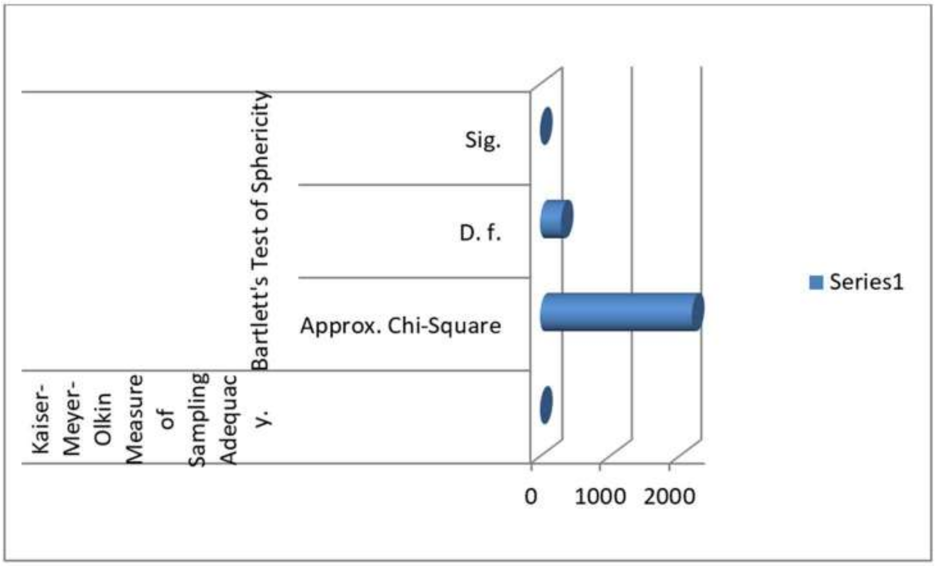
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.753
Bartlett's Test of Sphericity	Approx. Chi-Square	2184.789

Journal of Philanthropy and Marketing
Vol 3 No 1 (2023)
E-ISSN: 2691-1361

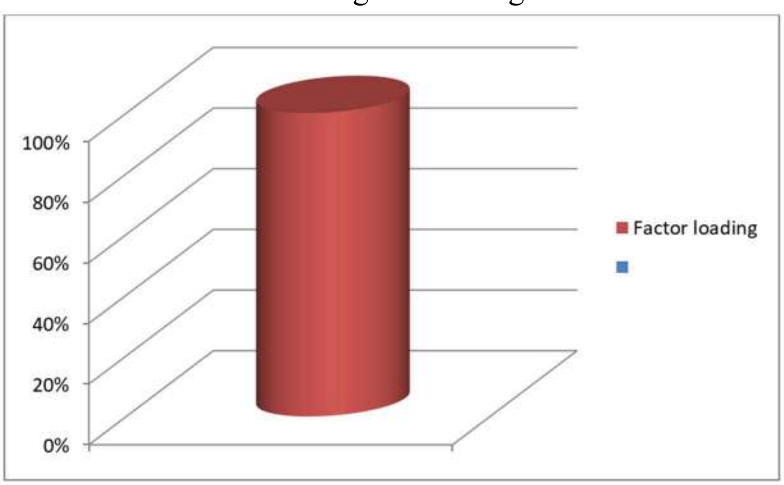
	D. f.	300
	Sig.	0

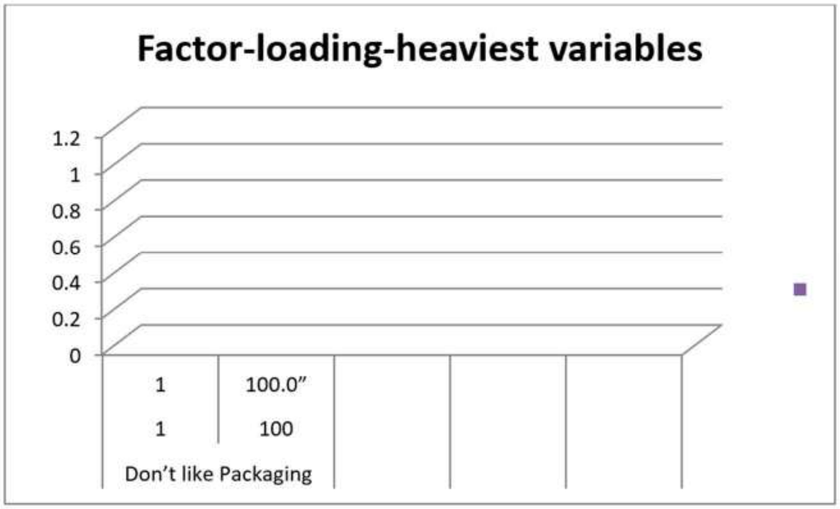
Source: Primary Data

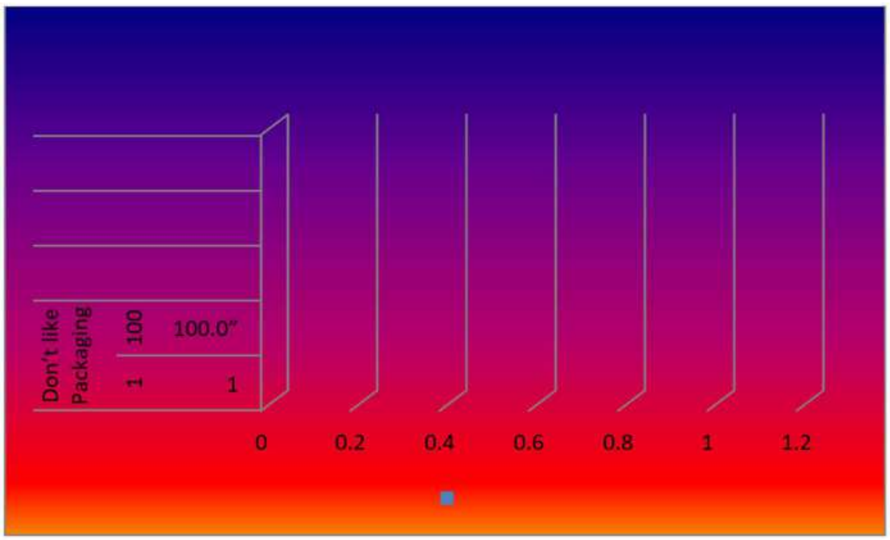
Table 3
Factor loading, consumer preferences for organic food products



The findings of a factor analysis performed on the 25 assertions (factors) stated concerning beliefs around the purchase of organic food are shown in Table 4. A total of twenty-five claims have been neatly categorised into the following five groups: perceived health, product characteristic, social welfare, product feature, and availability.
Here is Table 4 for the factors that have the highest loadings.





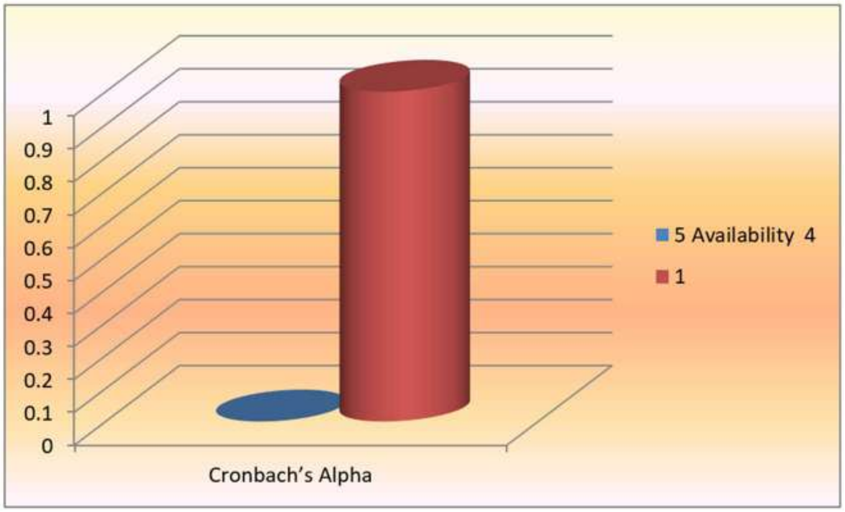


The factor analysis demonstrates that consumers' perceptions of organic food are influenced by the five criteria listed above.Variables loading on particular factors are used to identify the five factors. These factors' dependability scores are discovered to fall within allowable bounds.

Effects of Factors on Consumer Attitudes toward Organic Food Multiple regression is used to quantify how recognised factors affect consumers' purchasing decisions. Cronbach's alpha is used to assess each factor's items' level of reliability. The outcomes are shown in Table 5 below.

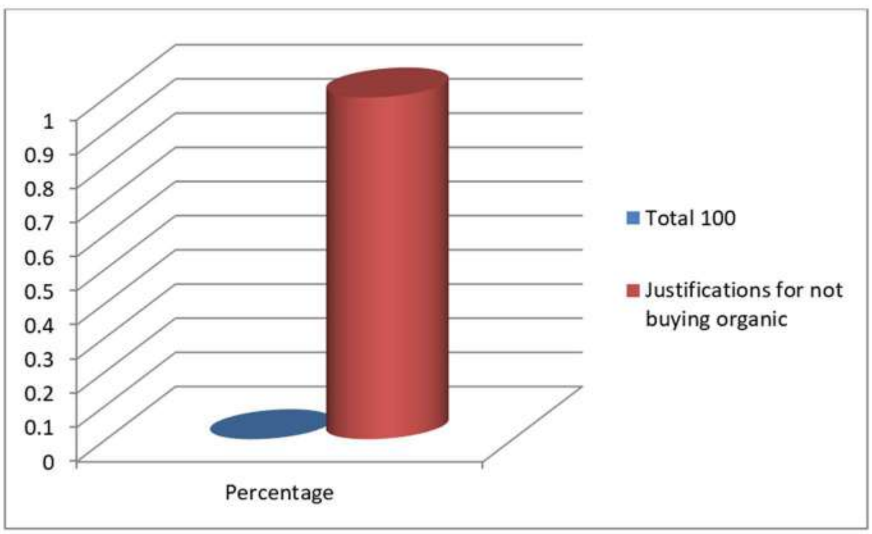
Table 5: Determinants of Organic Food Buying

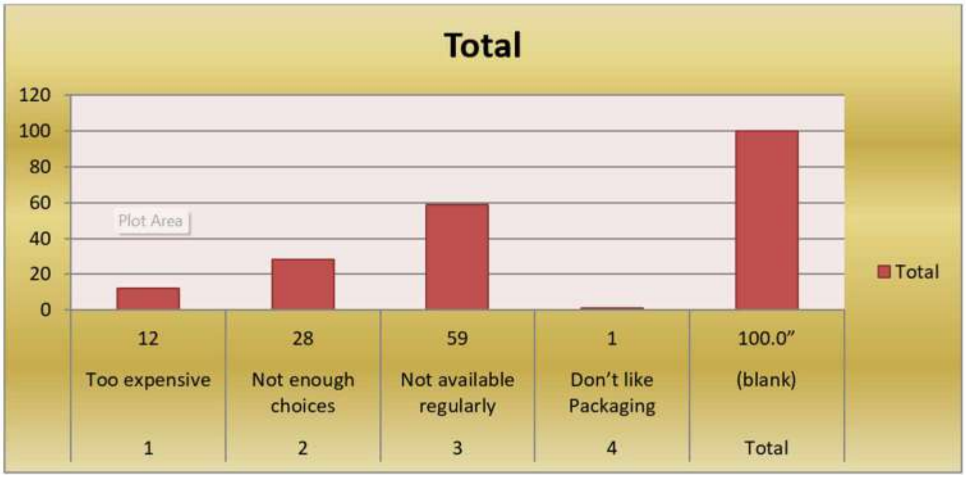
Vol 3 No 1 (2023)
E-ISSN: 2691-1361



According to the factor analysis, the aforementioned five factors have an impact on how consumers view on organic food. The five factors are found by looking at the variables' effects on particular factors. It is discovered that these factors' dependability scores fall within allowable bounds. Customers' preferences in organic product rankings.

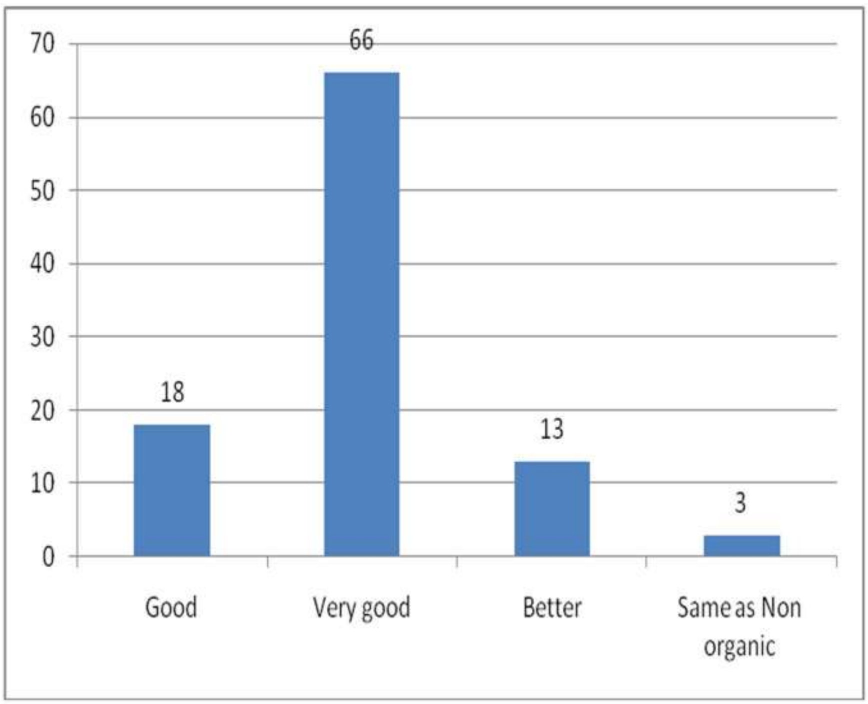
Justifications for not buying organic

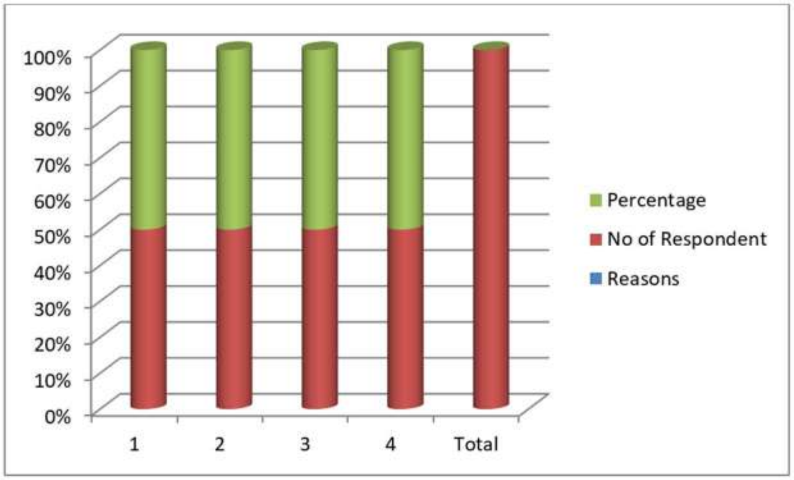




Results of the Research

1. According to the results of the survey, respondents have a number of issues while trying to shop for organic items in stores.





1. This section presents the study's findings.
2. Inconsistent supply is one of the biggest issues for those who choose to buy organic food. The organic shopper has been known to mix in some non-organic items with their organic purchases on occasion.
3. Unfortunately, organic goods are far more costly than their conventional counterparts. In order to discourage organic food buyers from stocking up on their favourite items.
4. There isn't a wide selection of organic goods on the market.
5. Consumers do not have sufficient knowledge about organic goods.
6. The organic items have not been verified as such by an official organic certification body.
7. Organic food options are scarce in the city.
8. As a whole, customers believe that the greater price of organic goods is justified.
9. 31% of organic product buyers fall within the 25-40 year old demographic.
10. Most people who buy organic goods have at least a bachelor's degree (54%), with 34% having just a high school diploma.
11. In Hyderabad City, out of 100 customers every one favoured organic items.
12. Sixty-four percent of shoppers regularly buy organic foods and goods.
13. The percentage of customers who shop at organic shops (where most food is sold) is high (76%) compared to the percentage who shop at conventional supermarkets (11%).
14. Sixty-nine percent of shoppers said they felt organic goods were too pricey.
15. Eighty-six percent of customers are willing to buy/consume the organic items, despite the high price, while just fourteen percent are unwilling to do so.
16. The survey found that organic product stores were the most common places where people may purchase organic goods.
17. One crucial factor that determines whether or not people buy organic items is their level of education. Based on the responses, it seems that all users are college educated at the very least.

Suggestions

- Consumers need to be made more aware of the benefits of buying organic goods.
- Organic food consumption would rise if product quality were steadily improved.

- Organic food sales may rise if people were exposed to ads for such foods more often and if their improved taste convinced them to switch to them. There is a correlation between the rise in consumer knowledge and the impact of advertising for organic food items.
- The factors of familiarity, personal philosophy, social contact, monetary cost, and ingrained behaviours were more influential in the decision to purchase organic food items.
- Customers' familiarity with organic food products is directly related to the marketing activities of the organic food industry. Organic food items need to be more widely advertised to increase their availability.
- Division of organic food sales at supermarkets into a distinct stock category
- Branding organic foods according to their unique qualities
- By shaping consumers' expectations about the value of organic foods, marketers may better position these items on store shelves.
- Products should debut in high-traffic areas of major markets before rolling out to the rest of the retail landscape.
- More people will be "Green Consumers" if they are educated about environmental issues and the advantages of using organic goods and eating organic food.
- They see "organic" as a product, but it will be marketed as a "way of life."
- There are agencies devoted to agricultural marketing and cooperatives that may assist farmers in receiving a fair price for their organically grown goods.
- With the support of the Organic Certification Department's seal of approval, producers may rest certain that their organic products are of the highest quality and thus command a premium price.
- The widespread availability of organic food items and their mass manufacturing in response to consumer demand should go hand in hand.

Discussion

The quality of output of a machine learning model depends on the purity of the data and the training of the model. In the present study, the data passes through rigorous data cleaning and pre-processing followed by model tuning and evaluations. Topic evaluation results indicated the presence of eight topics reflecting public attitude on organic foods. Except for Topic 1 and Topic 2, which discuss organic foods linking a specific incidence in the USA, all other topics highlight various aspects related to organic foods.The majority of previous studies on organic food consumption were based on tradi- tional, self-reported methods. These studies focused, for example, on consumers' moti- vations to buy organic foods, such as health, environment, and social consciousness. The only study based on content analysis of online comments about organic foods revealed 65 beliefs that the authors structured into 22 themes of a wide breadth, from 'price' to 'food security'. The authors structured them into four main categories: 'product', 'food system', 'authenticity', and 'production'. Our study contributes to this line of research by providing further structuring of public attitudes on organic foods based on objective techniques of big data and text mining. Moreover, based on the topic signifi- cance rank test, we have identified top the three most significant topics, i.e., plant-based diet, authenticity, and seasonality. The other significant themes related to organic food are organic farming and standardization, saving the planet, and food delivery. Our find- ings suggest also that people are quite enthusiastic about shifting to plant-based food. They believe that a plant-based diet can contribute to reducing greenhouse gas emis- sions. Dedicating natural resources such as land and water for growing plant-based foods can save the planet (Topic 6). Authenticity is another interesting theme. Under this theme, tweets indicated that a large group of people advocate organic food for being natural, healthy, non-GMO, and chemical and pesticide-free, while another group is skeptical about these claimed features of organic foods. On the 'seasonality,' people tweeted about the benefits of eating seasonal foods. Organic food eaters find seasonal foods fresh, tasty, and healthy. People in their tweets also highlighted the need for organic farming using the latest technology and standardization of food products and processes (Topic 7). The standards also aim to avoid false organic claims. Unfortunately, there are differences in standards across the countries. Further, Topic 8 discusses online delivery services and the availability of organic foods in local stores and markets.

Conclusion

People ignored the benefits of organic foods for a long time. More and more people are choosing organic foods over conventionally grown ones as a way to show their support for environmental protection. People were aware of the availability and representation of organic food products, but they did not necessarily remain loyal to them. Undoubtedly, inquiries about organic foods piqued the responder's interest. Organic food product marketers need to create campaigns that are ethical and realistic if they want to see results.Stores only have a limited amount of organically produced goods, despite the growing demand for them. The consumer's familiarity with organic products influences their perceptions and opinions of the product, which in turn impact their purchasing decisions. There are three foods that are now in high demand: vegetables, fruits, and beans. Compared to typical vegetables, the price of green vegetables is much higher. Customers are less inclined to buy a product when there is an unpredictable and small supply, a high price, and little information available about it.To understand what factors influence people to buy organic food, we may look at consumer behavior. Perceived health, product features, social welfare, product availability, and the capacity to purchase organic foods are the most influential variables on consumers. Organic food's nutritional value, natural components, food safety, availability, and availability awareness are some of the indirect reasons to buy it. People think organic food is good for them because of the significant correlation between how a product makes them feel and their actual health. Focus on guarantee certification and keeping the product's price low as perceived health is the least essential variable. People would choose organic food due to price, health, quality, and safety concerns, according to the survey. Since the consumer behavior towards organic food is changing rapidly due to awareness of environmental degradation, health hazards, and other related issues, this research started with an aim to answer the same existing question- how does the public view organic foods? Numerous studies have been conducted in the past. The majority of them are based on surveys and interviews, which are subject to various limitations such as social desirability bias, a response bias, and common method bias. In this study, we collected public posts from Twitter and utilized text mining techniques to extract the most discussed topics and sentiments towards organic foods. People willingly publish their opinions online on Twitter, which is free of an external bias. The findings obtained by utilizing the big data from social media platforms for text mining, provide relatively objective and verifiable results.The present study makes academic as well as practical contributions. From an academic perceptive, this is the first of early researches to study the public's attitude and sentiments towards organic foods using big data and text mining approaches." Also, this study adds to the existing literature by providing a broader and richer understanding of public perspec- tives on organic food consumption. The study explored public attitude on organic foods and identified underlying different emotions as opposed to just positive or negative sentiments.The results indicated the presence of negativity among the public mainly due to distrust in the authenticity of organic claims. Therefore, eliminating the distrust among the consumers may boost the growth of the organic food market. Thus, from a practical perspective, our findings can help policy-makers and certification bodies enhancing the communications about organic foods, thereby developing trust and positivity.

References

1. Wu Z, Zhang Y, Chen Q, Wang H. Attitude of Chinese public towards municipal solid waste sorting policy: a text mining study. Sci Total Environ. 2021;756:889.
2. Feizollah A, Mostafa MM, Sulaiman A, Zakaria Z, Firdaus A. Exploring halal tourism tweets on social media. J Big Data. 2021. https://doi.org/10.1186/s40537-021-00463-5.
3. Hemmerling S, Hamm U, Spiller A. Consumption behaviour regarding organic food from a marketing perspective— a literature review. Org Agric. 2015;5:277–313.
4. Danner H, Menapace L. Using online comments to explore consumer beliefs regarding organic food in German- speaking countries and the United States. Food Qual Prefer. 2020;83:9.
5. Robertson JL, Barling J. Greening organizations through leaders' influence on employees' pro-environmental behav- iors. Wiley Online Libr. 2012;34(2):176–94.
6. Stern PC. Toward a Coherent Theory of Environmentally Significant Behavior. Vol. 56, J Soc Issues. 2000. https://okat. pw/tuxas.pdf.
7. Poore J, Nemecek T. Reducing food's environmental impacts through producers and consumers. Science. 2018;360(6392):987–92.
8. Bar-On YM, Phillips R, Milo R. The biomass distribution on Earth. Proc Natl Acad Sci U S A. 2018;115(25):6506–11.
9. European Union. The EU's organic food market: facts and rules. 2020. https://www.europarl.europa.eu/news/en/ headlines/society/20180404STO00909/the-eu-s-organic-food-market-facts-and-rules-infographic
10. Hansen T, Sørensen MI, Eriksen MLR. How the interplay between consumer motivations and values influences organic food identity and behavior. Food Policy. 2018;74:39–52.
11. Molinillo S, Vidal-Branco M, Japutra A. Understanding the drivers of organic foods purchasing of millennials: Evi- dence from Brazil and Spain. J Retail Consum Serv. 2020;52:9.

12. Pham TH, Nguyen TN, Phan TTH, Nguyen NT. Evaluating the purchase behaviour of organic food by young consum- ers in an emerging market economy. J Strateg Mark. 2019;27(6):540–56. https://doi.org/10.1080/0965254X.2018. 1447984.

13. Iyer P, Davari A, Paswan A. Green products: Altruism, economics, price fairness and purchase intention. Soc Bus. 2016;6(1):39–64.

14. Hasselbach JL, Roosen J. Motivations behind Preferences for Local or Organic Food. J Int Consum Mark. 2015;27(4):295–306.

15. Kareklas I, Carlson JR, Muehling DD. I eat organic for my benefit and yours: Egoistic and altruistic considerations for purchasing organic food and their implications for advertising strategists. J Advert. 2014;43(1):18–32.

16. Chekima B, Oswald AI, Dr.Naveen Prasadula. Narrowing the gap: Factors driving organic food consumption. J Clean Prod. 2022;166:1438–47. https://doi.org/10.1016/j.jclepro.2017.08.086.

17. Sultan P, Tarafder T, Pearson D, Henryks J. Intention-behaviour gap and perceived behavioural control-behaviour gap in theory of planned behaviour: moderating roles of communication, satisfaction and trust in organic food consumption. Food Qual Prefer. 2020;81:103838. https://doi.org/10.1016/j.foodqual.2019.103838.

18. Tandon A, Jabeen F, Talwar S, Sakashita M, Dhir A. Facilitators and inhibitors of organic food buying behavior. Food Qual Prefer. 2021;88: 104077. https://doi.org/10.1016/j.foodqual.2020.104077.

19. Meiselman HL. A review of the current state of emotion research in product development. Food Res Int. 2015;76:192–9.

20. Ismael D, Ploeger A. Consumers' emotion attitudes towards organic and conventional food: a comparison study of emotional profiling and self-reported method. Foods. 2020;9:1.

21. Dr.Naveen Prasadula (2023)Review of Literature on Organic Options: A Study Of Hyderabad,Telangana Consumer Opinions Using Sentimental Analysis

22. Demetriou C, Ozer BU, Essau CA. Self-Report Questionnaires. Encycl. Clin Psychol. 2015;1:6.

23. Podsakoff PM, MacKenzie SB, Podsakoff NP. Sources of method bias in social science research and recommenda- tions on how to control it. Annu Rev Psychol. 2012;63:539–69.

24. Oatley K, Keltner D, Jenkins J. Understanding emotions. Malden: Wiley-Blackwell; 2006.

25. Weiss HM. No Title. In: Emotions in the workplace: Understanding the structure and role of emotions in organiza- tional behavior. 2002. p. 20–63.

26. Azadi, H., & Ho, P. (2010). Genetically modifi ed and organic crops in developing countries: A review of options for food security. Biotechnology Advances 28, 160-168.Bangladesh Organic Products Manufacturers Association (BOPMA) member list.

27. Baker, B., Benbrook, C., Groth, E., & Benbrook, K. (2002). Pesticide residues in conventional, integrated pest management (IPM)-grown and organic foods: Insights from three US data sets. Food Additives and Contaminants, 19, 427-446.

Vol 3 No 1 (2023)
E-ISSN: 2691-1361
28. Fillion, L., & Arazi, S. (2002). Does organic food taste better? A claim substantiation approach. Nutrition and Food Science, 32, 153-157.
29. Grunert, K. (2005). Food quality and safety: consumer behavior and demand. European Review of Agricultural Economics, 32, 369-391.
30. Kramol, P., Thong-ngam, K., Gypmantasiri, P., & Davies, W. (2006). Challenges in developing pesticide-free and organic vegetable markets and farming systems for smallholder farmers in North Thailand. Acta Horticulturae, 699, 243-251.
31. Madhan Kumar P., (2016), "The Effects of Consumer Attitude towards the Purchase of Organic Food Products in Sikkim", International , Journal of Advanced Research, 4(6): 20.
32. Saloni Mehra and Ratna (2014), "Attitude and Behaviour of Consumers towards Organic Food: An exploratory study in India", International Journal of Business Excellence, Vol 7 (6): 678.
33. Gupta, K.B. (2009), "Consumer behaviour for food products in India", International Food and Agribusiness Management Association, Budapest, Hungary.