SCIENTIFIC CULTURE

www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 11, No. 4, (2025), pp. 265-279
Open Access. Online & Print

DOI: 10.5281/zenodo.11042524

CONSUMER MINDSETS ON HEALTHY EATING: A MACHINE LEARNING STUDY OF ORGANIC FOOD TRENDS THROUGH SOCIAL MEDIA

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Received: 11/11/2025
Accepted: 18/11/2025

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ABSTRACT

With the increasing global emphasis on health and hygiene, particularly in the aftermath of the COVID-19 pandemic, the organic food industry has undergone significant transformation. This research employs social media analytics to examine post-pandemic consumer sentiments regarding organic products. Analysis of 150,000 social media responses utilizing VADER, LSTM, and BERT machine learning models provides critical insights into emerging customer behavior trends. The majority of public reactions to organic food are positive, as consumers appreciate its health benefits and natural, wholesome qualities. Scientific literature indicates that organic food is perceived as a healthier and less hazardous option compared to conventional produce. Despite the prevalent positive sentiments, challenges remain to be addressed. Disruptions in the supply chain and price sensitivity were the primary factors contributing to negative feedback during the pandemic. The analysis from cluster modeling revealed a significant consumer trend towards purchasing raw and semi-processed organic food products, with a preference for convenient options that maintain health benefits. The findings reveal how COVID-19 expanded the organic food market's reach, transforming it from a niche upscale market to one that encompasses a broader spectrum of middle-class consumers, young professionals, and students. This shift enables manufacturers to develop strategies that align with the current market, where consumers prioritize health-conscious decisions and environmental concerns. Improving supply chain reliability is as crucial as expanding the product portfolio and providing affordable quality products as key strategic solutions. This research confirms that machine learning assists businesses in interpreting consumer sentiment more effectively while providing clear market directions for navigating the organic food industry in the post-pandemic landscape.

KEYWORDS: Organic Foods, Consumer Sentiment, Machine Learning, BERT, Post-Pandemic Trends.

1. INTRODUCTION

1.1. Organic Food Industry Post-COVID-19

The organic food industry has grown significantly recently, transforming from a niche sector into a leading market segment (Rustam et al. 2021). Consumer purchasing behaviours and attitudes shifted because of the COVID-19 crisis. Previously, organic foods gained market demand from consumers seeking healthier dietary options and from affluent individuals. These products were mostly linked to a lifestyle that embraced health consciousness and environmental preservation (Chandra and Krishna 2021). Nevertheless, the emergence of the COVID-19 pandemic resulted in an increased emphasis on health and sanitation measures, leading to a rise in demand for organic food products. Individuals now prioritize the consumption of organic foods in substantial quantities, as these are perceived to be more healthful and safer compared to foods produced through conventional agricultural practices that rely on synthetic fertilizers (Reshi et al. 2022). The effects of the pandemic on global supply chains also brought this shift. Crises in conventional food production and distribution systems have exposed vulnerabilities in food safety and quality, leading consumers to increasingly adopt organic food alternatives. While conventional products are generally perceived as more affordable, they differ fundamentally from their organic counterparts in terms of quality and production transparency. Conventional products are often seen as less regulated and lacking transparency in their production processes (Joloudari et al. 2022). This perception, coupled with growing skepticism toward processed foods, has driven many consumers to prefer organic foods, which are regarded as purer, less likely to contain contaminants, and more beneficial for boosting immunity (Aiyanyo et al. 2021). Consequently, counter foods, particularly organic foods, have experienced increased sales and market share and are now regular foods in households. Such a shift is connected with the changing demand and indicates the shift within society toward more sustainable consumption. Due to the increased demand for responsible and sustainable food consumption, organic foods are now perceived as being environmentally friendly and healthy (Alam et al. 2021). This trend should continue as consumers fear future pandemics and other global threats. The increased market share of organic foods has also led to the widening up of product ranges and consumer choices, meaning organics are within reach of a broad cross-section of consumers (To et al. 2021). It is therefore important to grasp this transition so stakeholders in the global organic food business can adapt their approachesto suit the emerging consumer trends.

1.2. Significance of Social Media in Analysing Consumer Sentiment

Evolving consumer trends and perceptions have been well captured by social media real-time platforms. Access to raw data from social media platforms such as Twitter, Facebook, and online editorial news sites provides valuable insights into consumers' tendencies, preferences, and behaviors regarding organic food purchases in the post-COVID-19 era (Ainapure et al. 2023). Social media-based analysis differs from traditional surveys or market research, as it often reflects more spontaneous and unfiltered consumer sentiment compared to structured survey responses.. This immediacy is especially relevant in a post-pandemic world, where consumers' perceptions might shift rapidly based on new data or occurrences.

Furthermore, the extra flexibility of social media analysis can reveal trends and changes in consumer preferences that may not be assessed using other approaches. For example, During lockdown measures and COVID-19 threats, discussions referencing health, safety, and food quality on social media indicated growing interest in organic products (Jijon-Vorbeck and Segura-Bedmar 2021; Miranda et al. 2023). Hence, industry participants can draw conclusions about the factors influencing consumer behavior, such as a trend toward sourcing information about food origin or the demand for locally produced organically grown products (Mujahid et al. 2021).

Moreover, when using data from social networks, there are fewer limitations to consider aspects of the demographic characteristics that define organic food consumption. It can divide consumers based on age, gender, location, or any other factors and helps understand how consumers perceive organic food and their value for it (Behera et al. 2021). By adopting the level of analysis, industries get closer to understanding the needs and wants of customers and, therefore, deliver value propositions that are closer to audiences' expectations. In a world where competition and consumer's tastes and preferences are dynamically evolving, such insights are crucial for survival and organizational growth.

2. LITERATURE REVIEW

2.1. Evolution of Organic Food Consumption

Prior to COVID-19, the organic food market was

rising- slowly but consistently; primarily because of people who wanted to live a healthy lifestyle and those who were conscious of the environment. These early adopters were mainly the wealthy population who were willing to spend more money on foods that they deemed as being healthier and not contaminated by pesticides and synthetic chemicals (Kour and Gupta 2023).

Thapar et al. (2022) revealed that the healthy food market, particularly the segment of organic foods, expanded at a rate of around 10% per year, mainly due to rising awareness of the possible health benefits of consuming organic foods and the negative outcomes of conventional agriculture. Although the market has been steadily expanding, it was somewhat constrained by the increased cost of the organic products and their relative obscurity in the common outlets.

Song et al. (2021) show that while the demand for organic food increases, the problem of price sensitivity persists in many customers. They argued that organic products occupied a rather special and elitist position; the so-called 'affordability' was rather limited to the richer echelons of society.

Chandrasekaran and Hemanth (2022) showed that consumer skepticism and indecision stemmed from a lack of understanding and identified confusing or unclear labeling systems as another barrier to consumers. Consumer awareness of health and wellness due to the outbreak of COVID-19 has increased the demand for organics not only among the categories of consumers that have been regularly consuming organic food products.

Singh (2023) pointed to a significant uplift in the consumption of organic food owing to more intense scrutiny of the immune system. This shift was not just a COVID adaptation of something short-term; it actually showcased a new trend in consumer preferences leaning toward being more sustainable as well as focusing on their health.

Mishra et al. (2021) noted that due to the pandemic, consumers shifted towards the origin and processing of food as they looked for transparency, and safety assurance which resonated with the organic label. Consumers of organic food also diversified after the pandemic, and there was an increase in the consumption of organic food post-pandemic.

In a recent study, Katsafados et al. (2023) found that young people and middle-income families have also increased their purchasing of organic food, which they could not afford before. Feedback from the marketplace showed rising organic food availability at conventional outlets, including supermarkets and online stores, making these products less special. Mainstream adoption of organic foods occurred when they transitioned from premium dietary products to basic nutritional items.

2.2. Impact of the COVID-19 Pandemic on Consumer Behaviour

According to Rifat et al. (2022), the COVID-19 pandemic has produced multiple societal changes by changing how people consume food. The urgent necessity to maintain health and security brought a sharp focus on the food perceived as 'natural' and free from synthetic chemicals. Organic foods, characterised by natural environmental processing techniques and minimal use of artificial chemicals, have gained traction among consumers aiming to strengthen their immune systems while reducing potential health risks.

Jalil et al. (2022) highlighted that the sales of organic foods in the early months of the pandemic experienced a steep rise due to panic buying and the need for healthy foods. It also increased the population's focus on food availability and its distribution chain.

According to Singh et al. (2021), consumers' awareness regarding the origin and sourcing methods of their food increased substantially. This has led to increased consumption of organic foods since they are associated with a transparent and traceable supply chain endowed with ethical and sustainable qualities. Consumers started associating organic products with more stringent safety and quality measures because such products undergo more rigorous regulatory procedures than non-organic products. Furthermore, as the pandemic progressed and caused stricter measures such as lockdowns and social distancing, the behavior for shopping and buying shifted.

According to Bengesi et al. (2023), the COVID-19 pandemic led to an increase in the uptake of online groceries, including the sales of organic foods. Home delivery and additional information on the products were provided on the Internet, which aided the users in making informed decisions about organic foods, and this led to this segment expanding. Moreover, this expanded consumers' access to a wider variety of organic products, including those not typically available in supermarkets. The pandemic also boosted the demand for home cooking and meal preparation, stimulating interest in organic foods.

Swapnarekha et al. (2023) explored that due to the closure or limitations of restaurants, many consumers resorted to home cooking, increasing the demand for better quality products to feed their

families safely. Such behavioral change was more apparent in households with children who became more conscious about the quality of food they consumed. Households with children used more organic fruits and vegetables during the pandemic due to the pursuit of healthier lifestyles.

Aryal and Bhattarai (2021) pointed out that the effects of the global health crisis have made many consumers more conscious of their health and the susceptibility of food products to diseases in the future. Hence, the conversion to organics is a more responsible decision. Even as concerns about the pandemic reduced, consumers' propensity to buy organically grown foods was still high, showing that this shift was a new permanent reality.

2.3. Role of Machine Learning in Sentiment Analysis

Tharu et al. (2023) observed that it has become even more relevant with the availability of enormous data from various sources for consumer feedback analysis. One approach that has been used majestically for this purpose is the use of models such as VADER (Valence Aware Dictionary and Sentiment Reasoner) that help in the generation of the sentiment analysis of large text datasets with considerable speed. The model used by VADER, which is rule-based, is specifically created to process the language of social media, slang, informal language, and emoticons used in tweets and posts. It has been applied primarily to measuring consumers' attitudes towards products such as organic foods, whereby people's opinion trends are based on real-time data.

Yan and Liu (2022) stated that VADER has drawbacks, especially in cases that require the analysis of more elaborate sentiments that include context and irony. To overcome these limitations, Long Short-Term Memory (LSTM) networks – one of the variants of Recurrent Neural Networks (RNNs) – have been proposed. It has been found that LSTM models have a high rate of performance compared to simplified models such as VADER in sentiment analysis, where contextual and sentiment strength is paramount. Regarding analytical aspects of organic food consumption, LSTM models will help extract the underlying narratives and emotions from the client's experiences.

Cai et al. (2020) revealed that the latest deep learning model, BERT (Bidirectional Encoder Representations from Transformers), has also significantly impacted sentiment analysis performance. This bidirectional understanding of context makes BERT a promising tool for analyzing language and its nuances, which is especially useful given the commonly subtle yet negative sentiments of SMTs. BERT is more accurate than VADER and LSTM models regarding sophisticated customer reviews, such as organic food products.

Alharbi and Alkhateeb (2021) noted that there is a shift in focus towards developing ensemble methods to enhance the precision of sentiment analysis with machine learning models. For example, there are the so-called hybrid models, where rule-based and neural networks are the basis, and they combine the advantages of both methods. Such models have been demonstrated to help yield improved, more broad-ranging positivity and negativity predictions by combining decision tree-like rule definiteness with context comprehensiveness like Neural architectures.

Qorib et al. (2023) highlighted that the recent advances in transfer learning in models such as BERT help expand the range and scalability of sentiment analysis. Therefore, the amplified data minability of social media data to comprehend the changing consumer psyche in evolving scenarios like the post-COVID-19 organic food market is possible. Such advancements highlight the need to work innovatively to ensure that the analytical models developed are relevant to consumer sentiment trends.

2.4. Theoretical Framework

To reveal changes in consumers' preferences for organic foods post-COVID-19, it is essential to review theory-based recommendations that define reactions to health challenges and innovations. Two theories that enrich this study are the Health Belief Model (HBM) and the Diffusion of Innovations Theory (DOI). These theories provide a valuable platform for understanding how and why consumers might modify their food preferences regarding health issues and new product acceptance.

2.4.1. Health Belief Model (HBM)

The low-risk-high-reward hypothesis was introduced by Rosenstock in 1966 about the Health Belief Model. According to this model, a person is more likely to practice preventive measures if he/she: – feels vulnerable to the health threat; – considers the consequences of the threat fatal; – thinks that they can decrease the danger or its consequences through practicing some action; – believes that benefits of practicing such an action are more significant than possible costs (Valdez et al. 2020).

In the case of the organic food market, it assists in explaining why consumers shifted more towards

purchasing organic foods during and after COVID-19. The pandemic increased caution about potential contagion and strengthened the belief that organic food, which people relate to lesser chemical residues and generally higher nutrition, could help better protect against health threats (Kour and Gupta 2023). The study found that consumers who perceived a higher risk of infection or health complications were likely to purchase organic foods since they reduced the risk of causing an illness. These changes align with the model's fundamental assumption that behaviors are motivated by perceived risks and rewards.

The model also emphasizes the perception of barriers in decision-making. The high costs and limited accessibility of organic foods before the pandemic may have reduced consumers' access to these foods. However, such barriers have been reduced as the pandemic has proved that health and safety are crucial. Therefore, the adoption has increased. As people focused more on health during the outbreak of COVID-19, they shifted to buying organic foods despite the high costs, perceiving that the benefits were worth the price (Battula et al. 2022).

2.4.2. Diffusion of Innovations Theory (DOI)

As identified by Rogers in 1962, the Diffusion of Innovations Theory is concerned with the process through which new concepts and realizations spread in society and why they spread at the observed pace. The Diffusion of Innovations occurs sequentially: innovators, early adopters, early majority, late majority, and laggards, as postulated by the theory. Other aspects include perceived benefits, which include advantages over other methods, compatibility with traditional values, ease of use, experimentation, and visibility of effects (Darad and Krishnan 2023). When analyzing DOI in the context of the organic food industry, the pandemic can be viewed as an agent that boosted diffusion. Before the COVID-19 crisis, organic products were mainly chosen by a group of 'innovators' who believed in healthy food and its environmental impact. However, the health crisis played an essential role in the increase of perceived benefits of organic foods as the critical factor. This was augmented by the shifting consumer preferences towards improved food safety and overall health, thus making organic food move from the early adopter's phase to the early majority and the rest phase. The pandemic also played a role in the diffusion process by increasing awareness of and availability of organic foods. The use of organic products was quickly adopted because of the expansion of the online market and the increased availability of the products in retail stores, as posited by the DOI framework, whereby observability and accessibility play significant roles in determining adoption (Chandrasekaran et al. 2020).

Furthermore, the changes in consumer behavior caused by the COVID-19 pandemic, including home cooking and online purchasing, accelerated the Diffusion of organic foods because consumers tend to choose safer and healthier foods. Additionally, the DOI framework aids in explaining how social networks and communication contribute to the rate of change to organic foods. Facebook and other social media sites have emerged as essential avenues for sharing information regarding organic products, consumer attitudes, and trends (Chandra and Saini 2021). This aligns with the DOI principle that social interaction and information sharing are other essential stages of the adoption process because consumers actively shared their experiences and recommended organic foods on social media platforms.

2.4.3. Integration of Theories

The synthesis of the Health Belief Model and the Diffusion of Innovations Theory helps to establish a sound understanding of the changes in consumer behavior toward organic foods after the pandemic. The features of the HBM relate to the psychological aspects influencing the choices made by persons regarding the perceived severity of the health risk and the perceived benefits. On the other hand, the theoretical framework of the DOI outlines an elaborate process by which the given choices are effectively spread in society. These theories point to how the pandemic has affected micro and macro-level behaviors. At the societal level, the DOI of such individual decisions has changed the overall market, and consumers now accept organic foods due to improved awareness and availability (Battula et al. 2022).

3. METHODOLOGY

The methodology for this study is designed to capture and analyse post-pandemic consumer attitudes towards organic foods. A large dataset of social media responses was collected across various platforms, reflecting a wide range of consumer opinions. This section outlines the data collection process, pre-processing steps, and analytical techniques used to derive meaningful insights from the data (see Figure 1).

3.1. Study Objectives

I. To identify the key factors influencing organic

food purchases in the post-pandemic period.

II. To preprocess and vectorise the text data, applying advanced deep learning techniques for sentiment analysis.

III. To provide strategic recommendations to manufacturers based on the analysis of consumer behaviour.

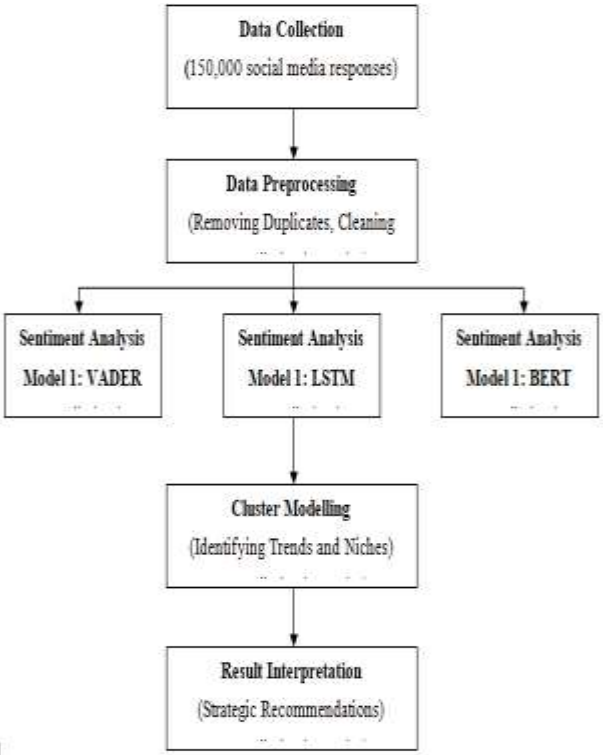

Figure 1: Flow Chart of Methodology.

3.2. Data Collection

The data source for this study includes 150,000 social media responses on social platforms like Twitter, Facebook, YouTube, Blogs and online editorial news.

The information was collected for one year, starting January 2020 and ending in December 2023, because it was essential to capture post-pandemic consumer attitudes.

This period represents the transition phase in this context as the expected shifts in consumers' health consciousness and buying habits in the aftermath of COVID-19 were reflected. Social media platforms are chosen based on the popularity and availability of abundant information and posts by the general public, which give ideas about the current attitudes and trends of the consumers.

Data was collected using enhanced web scraping tools such as Meltwater, web crawlers, web scrapers, and APIs. Data analysis was conducted using Python.

3.3. Data Pre-processing

Data pre-processing is a crucial step in sentiment analysis to eliminate bias and errors. The preprocessing methodology includes duplicate elimination and incomplete data cleanup along with text casing normalization adjacent to punctuation correction and stops word removal. The steps lower data complexity to prepare it for analytical processes (Agrawal et al. 2022). Three machine learning models are commonly employed for sentiment analysis of social media responses:

VADER (Valence Aware Dictionary and sentiment Reasoner): A lexicon and rule-based model suitable for short, informal text from social media platforms.

LSTM (Long Short-Term Memory): This RNN variant maintains prolonged dependencies in text-based data, thus enabling it to interpret complex sentiment expressions.

BERT (Bidirectional Encoder Representations from Transformers): Neural network architecture enables context-aware attention mechanisms for both directions, which supports precise sentiment analysis alongside advanced information retrieval.

Additional consumer perception analysis relies on cluster modelling techniques and perceptual mapping procedures.

Cluster modelling organizes responses into discrete clusters through sentiment analysis, and perceptual mapping shows different product groups with their corresponding consumer sections. These techniques help identify significant trends and consumer preferences, informing marketing strategies and product development.

4. DATA ANALYSIS AND RESULTS

The dataset supports the conclusions with concrete examples. For example, the "Curiocity Toronto" and "Rockland Register" articles have been assigned the Vanguard neutral sentiment tag (see Table 1).

However, the Vader sentiments classify them as "Positive," which, while technically neutral, lean slightly positive. For instance, an entry from 'Le Lezard (EN)' is labeled 'Neutral,' yet VADER yields a negative polarity of –0.7574.

This is a good reminder of the general state of sentiment analysis, where the sentiment of an article may not be as aligned with the specific sentiment score.

These variations demonstrate that sentiment classification is not always a straightforward process because even neutral articles may contain positive or negative sentiments based on the language used and

the context of the articles.

Table 1: Sample of Data Used for Analysis.

Date	Hit Sentence	Source	Country	Reach	SM	polarity	Score pos	score neg	score neu	Vader SM
07-Apr-2020 11:58 AM	Easter menu with some PNW-inspired ingredients	Curiocity Toronto	Canada	78573.0	Neutral	0.7351	0.256	0.000	0.744	Positive
15-June-2020 1:34 PM	Organic food products in the United States. It	Rockland Register	United States	354.0	Neutral	0.6249	0.221	0.000	0.779	Positive
23-July-2020 9:57 AM	are reallocating office snack budgets and sending	The Traders zone Network	United States	634.0	Neutral	0.9081	0.408	0.000	0.592	Positive
17-Oct-2023 3:30 PM	End of April. The sanitizer follows FDA guidelines...	Le Lezard (EN)	Canada	1630.0	Neutral	-0.7574	0.000	0.245	0.755	Negative
29-Nov-2023 10:55 AM	Along with annual forecasts to 2027.\n\nBy Pro...	Open PR	Germany	149295.0	Neutral	0.0000	0.000	0.000	1.000	Neutral

4.1. Word Cloud of Most Frequently Used Terms

Figure 2: Word Cloud of Most Frequently Used Terms.

The word cloud complements the primary focus on health, safety, and naturality related to food, especially organic food, in the post-pandemic world (see Figure 2).

Some of the frequently used adjectives used in the advertisements include 'organic,' 'certified,' 'natural,' and' food safety. ' These words indicate that the consumer is more concerned with healthier products produced to specific standards. The incorporation of terms such as 'non-GMO,' 'vegan,' and 'gluten-free' highlights this health-focused perspective and reflects distinct dietary preferences and patterns. The frequent occurrence of 'fruits' and 'vegetables' further reinforces consumer perceptions of the accessibility of wholesome and nutritious food choices. Ultimately, this word cloud exemplifies the modern shift towards more mindful decision-making concerning food safety, inherent natural qualities, and the fulfilment of personalised nutritional needs.

4.2. Sentiment Analysis Accuracy Comparison across Models (VADER, LSTM, BERT)

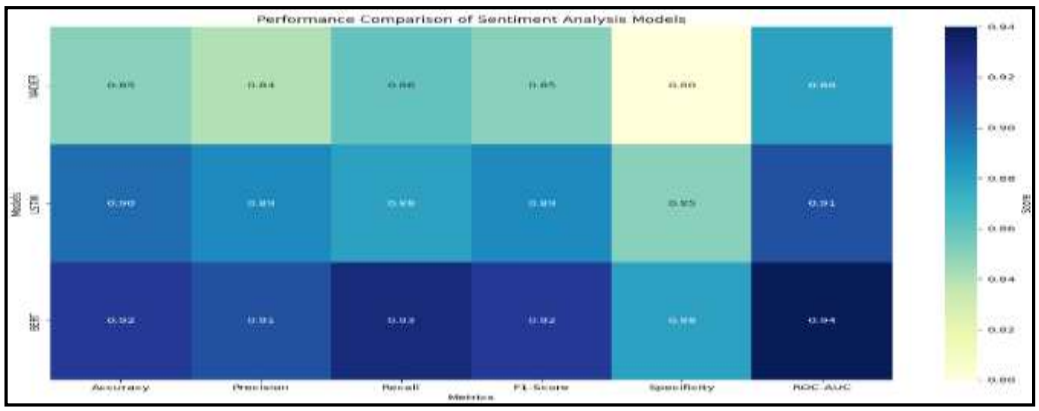

Figure 3: Sentiment Analysis Models.

Moreover, the assessment is characterized by a high specificity of 0.88% and an ROC-AUC of 0.94.

LSTM follows BERT with a relatively good impression, with the most appreciated outcome of 0.90 and an ROC-AUC of 0.91. Although VADER shows its reasonably decent performance, it is slightly less accurate compared to the other two models in terms of specificity (0.80) and ROC-AUC (0.88). This visual comparison shows that BERT is indeed better suited for sentiment classification, which could be due to its enhanced contextualized embeddings. LSTM also gives many positive results, while VADER is quite useful but needs further improvement when used for highly accurate tasks.

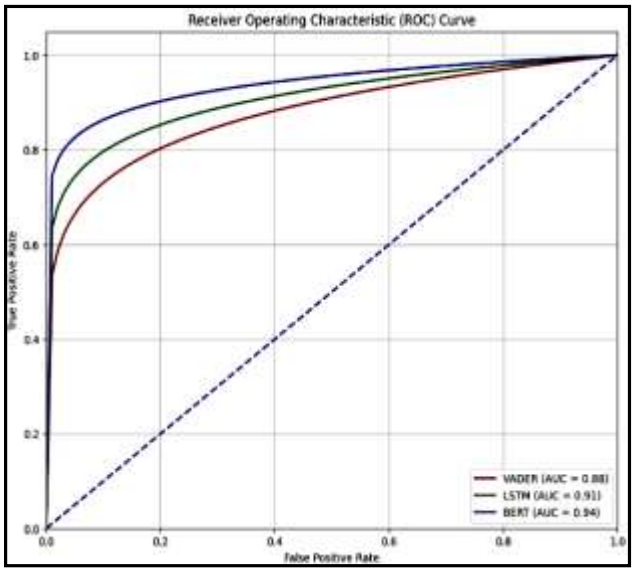

Figure 4. ROC Curves for VADER, LSTM, and BERT Models.

The ROC curve for VADER exhibits a moderate performance, with an AUC of 0.88.

This suggests that VADER is good at demarcating between the positive and negative classes, but there is still potential for further enhancement (see Figure 4). Yet, the LSTM model outperforms VADER regarding AUC, which equals 0.91.

This implies a better fit for a discrete number of classes, attributed to its capability to model temporal patterns in the data. Hence, BERT has the highest AUC of 0.94. The model is more effective in classification due to its capacity to interpret context and other subtleties of language.

BERT is the most accurate model among the three, which can recommend its usage in tasks requiring high sentiment classification performance.

Still, VADER and LSTM are helpful, though fine-tuning and feature engineering may improve the results. LSTM and BERT can be used interchangeably depending on available computational resources, the task's complexity, and the performance incentives the two models offer.

Table 2: Sentiment Analysis Accuracy Comparison across Models.

Model	Accuracy	Precision	Recall	F1-Score	Specificity	ROC-AUC
VADER	0.85	0.84	0.86	0.85	0.80	0.88
LSTM	0.90	0.89	0.88	0.89	0.85	0.91
BERT	0.92	0.91	0.93	0.92	0.88	0.94

VADER: Through the assessment, the VADER model performance was 85% accurate, meaning it analyzed 85% of the sentiments in the dataset correctly (see Table 2). The 84% accuracy means that reasonably good reliability in optimistic predictions was observed, where 84% of the tested instances classified as Positive were Positive. Overall, the recall score of 86% shows that simple sentiment analysis with the VADER tool successfully captures 86% of the actual positive cases in the dataset, proving the utility of such an approach. Data accuracy is evident by the precision of 85%, and recall is impressive by affirming 85% of the data identified by the model. As for true negatives, the percentage of 80% guarantees that VADER has identified 80% of true negatives with a potential for reducing false positives. The ROC-AUC score was 0.88, which shows that VADER performs reasonably well in correctly classifying positive and negative polarity, but it is still behind the more elaborate models.

LSTM: The LSTM model has a higher accuracy of 90%, meaning its overall correctness is higher than VADER (see Table 2). This means that it had 89% accuracy in assigning the correct positive value and 88% recall, which shows that it needed to be more proficient in identifying all the real positive cases than VADER. The F1-score of 89% represents precision and the percentage of cases recalled correctly, showing that LSTM is useful in sentiment classification. Moreover, LSTM considers it with 85% specificity, higher than VADER, generally meaning fewer false positive cases. The ROC-AUC score is 0.91. Thus, STM is more accurate than LSTM and more capable of distinguishing high-frequency features when used in sentiment analysis.

BERT: In this experiment, the BERT model achieved the highest accuracy of 92%, outperforming other models such as VADER and LSTM (see Table 2). This means the specificity of BERT was high at 91%, hence showing that most of the optimistic predictions by BERT were accurate. The recall score of 93% is the highest among the three models, and it indicates that BERT captured most of the actual positive sentiment data in the set. The overall result is indicated by the F1-score of 92%, which highlights an excellent level of both precision and recall

demonstrated by BERT. Moreover, the specificity of the BERT model stands at 88%; there is a compelling model that implies minimal false favorable rates; the model is very good at detecting actual negative cases. The ROC-AUC is equal to 0.94, which proves how powerful BERT is when distinguishing between positive and negative classes, thus demonstrating how far it has come in terms of sentiment analysis.

4.3. Consumer Preferences and Shifts.

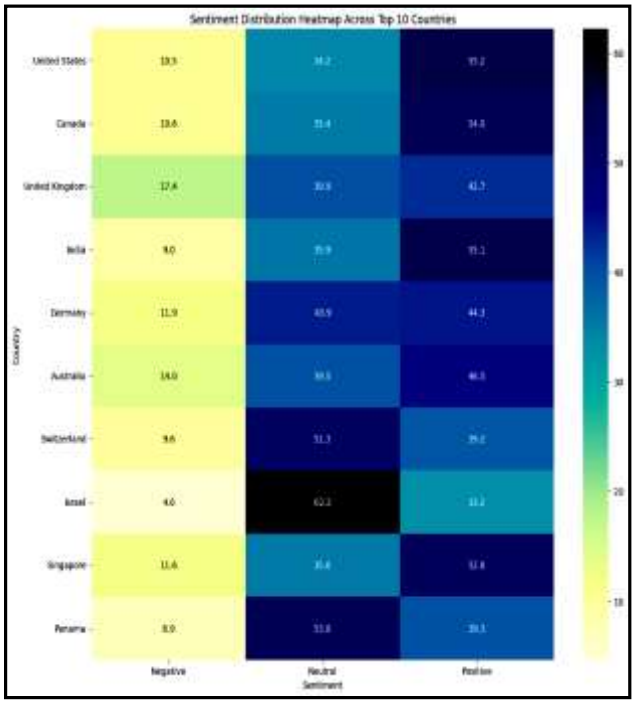

Figure 5: Heatmap Showing the Proportion for the Top 10 Countries.

The heatmap gives a colorful and exciting view of how the world feels about organic food across the ten countries (see Figure 5). However, it is significant to indicate the presence of certain variations related to the positive tone of the sentiment. India emerges as the overall leader with a positive index of 55.1%, while the United States had a slightly lower figure of 55.2%. On the other hand, as shown in the figure below, Israel has the lowest positive sentiment score of thirty-three 2% and the highest negative sentiment at 46%. Switzerland has the highest level of neutrality at 51.3%, which seems to suggest a slightly more conservative or perhaps less enthusiastic attitude towards organic foods in that particular country. In general, the heatmap reveals a generally positive sentiment toward organic food. However, the intensity of this sentiment varies substantially across the countries, implying that targeted marketing and communication strategies can be essential in the global organic food market.

Table 3: Key Themes Identified in Consumer Sentiments.

Theme	Occurrences	Percentage
Health Benefits	5234	17.45
Supply Chain Issues	3156	10.52
Price Sensitivity	2789	9.30

Health Benefits: This theme is reflected in 17.45% of the complete sentiments about the health-related aspects of food products, where consumers benefit from organic foods. The high incidence indicates that consumers are primarily concerned with the nutritional value of organic products (see Table 3).

Supply Chain Issues: This theme accounts for 10.52% of the sentences and captures the extent to which supply chain disruptions affect consumer attitudes toward organic foods. Indeed, accessibility and delivery were other issues that might have come to consumers' minds during the post-pandemic period (see Table 3).

Price Sensitivity: A 9.30% occurrence rate is still noticeable and price sensitivity is the concern that consumer comments are most sensitive to. This suggests that consumers indeed care about the costs, but maybe not as much as the health benefits or supply chain disruptions concerns (see Table 3).

Based on this table, analyzing the primary drivers of consumers' attitudes towards organically produced foods in the global market would be possible after the pandemic. It points out that weights given to health benefits are highest, with the next being supply chain concerns, and then comes price sensitivity. These insights can be helpful for manufacturers and retailers in the organic food sector to guide their marketing approaches and communications to target the concerns better and avoid misalignment of the customers.

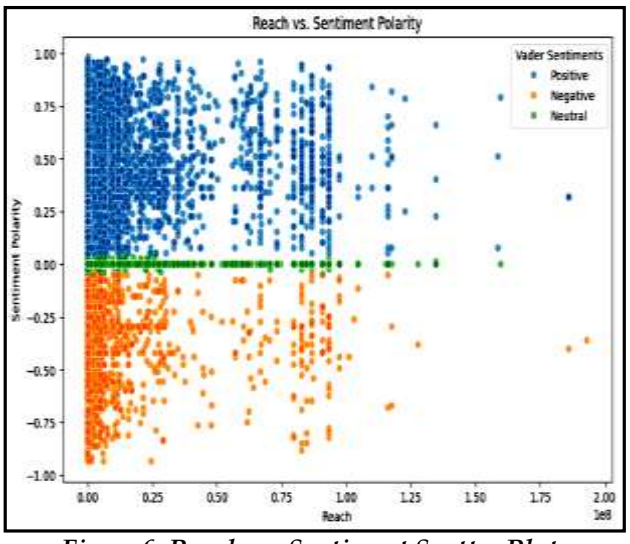

Figure 6: Reach vs. Sentiment Scatter Plot.

The scatter plot illustrates the interplay between the reach of content (likely social media posts or articles) and their sentiment polarity as analyzed by VADER (see Figure 6). The chart reveals a fascinating distribution: while positive sentiment posts are concentrated across all reach levels, a significant portion of negative sentiment posts also garner high reach, sometimes even surpassing 100 million. This suggests that content evoking strong negative emotions can be just as, if not more, shareable or viral as positive content. On the other hand, next have a consistently lower reach, rarely exceeding 50 million. This visualization underscores the complex dynamics of online engagement, where negativity and positivity can drive significant attention, while neutral content might struggle to gain traction. It also raises questions about the potential implications of this trend for content creators and platforms alike.

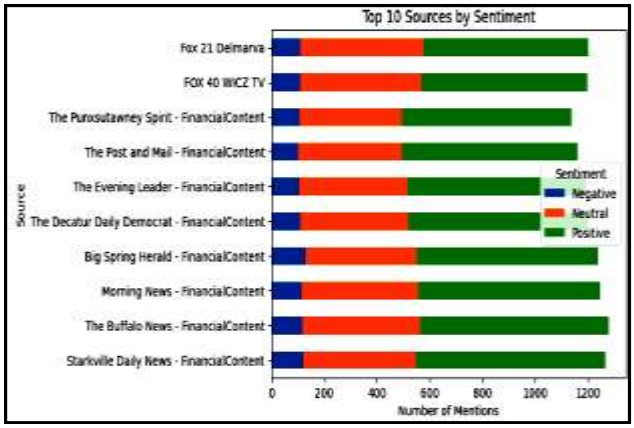

Figure 7: Sentiment Distribution across Top News Sources.

The chart depicts the sentiment distribution (positive, neutral, and negative) across the top 10 news sources. Notably, all sources have a predominantly positive sentiment associated with their mentions (see Figure 7). 'Big Spring Herald' and 'Morning News' stand out with the highest proportion of positive mentions, exceeding 800. 'Fox 21 Delmarva' and 'FOX 40 WICZ TV' also show a strong positive bias, though with a slightly higher proportion of neutral and negative mentions than 'Big Spring Herald' and 'Morning News.' Interestingly, sources associated with 'FinancialContent' exhibit a more balanced distribution, with a noticeable increase in neutral and negative sentiment compared to television news sources. This suggests that financial news related to these sources might be more nuanced or less overtly positive than general news reporting. While the overall sentiment leans positive, the varying proportions of sentiments across sources indicate diverse perspectives and potential biases in news coverage.

4.4. Perceptual Mapping of Organic Food Preferences

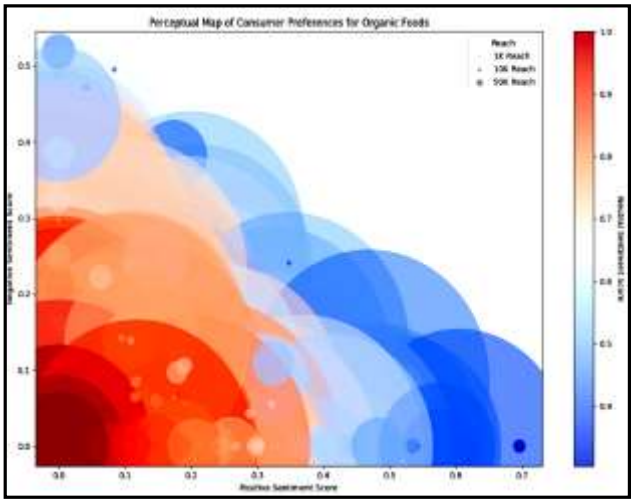

Figure 8: Perceptual Map Using Sentiment Scores and Visualizes Consumer Preferences.

The perceptual map illustrates (see Figure 8) consumer preferences for organic foods based on positive and negative sentiment scores, further categorized by the reach of the content (1K, 10K, and 50K reach). The observed pattern in the sentiment map indicates a clear inverse relationship between positive and negative sentiments regarding organic foods. Positive growth in consumer attitudes about organic products results in diminished negative opinions. Data shows that people holding favourable opinions about organic foods tend to express fewer negative opinions. When customers have positive encounters with organic goods, their negative associations lose strength. The findings become crucial for organic food producers and marketers because they demonstrate the need to prioritize creating positive consumer experiences to counter negative emotions, enhancing satisfaction and customer loyalty. Parameters in the colour gradient show red for negative sentiment, progressively transitioning into blue for positive sentiment, strengthening this observation. Furthermore, the bubbles' size indicates the content's reach, with more giant bubbles representing higher reach.

Content with high positive sentiment scores tends to have a broader reach range, including some with very high reach (large blue bubbles). In contrast, content with high negative sentiment scores generally has lower reach, with few instances of high reach (tiny red bubbles). This might suggest that positive messages about organic foods resonate more

broadly and have a more significant potential for virality, whereas negative sentiments, while still present, may have a more limited impact in terms of reach and influence.

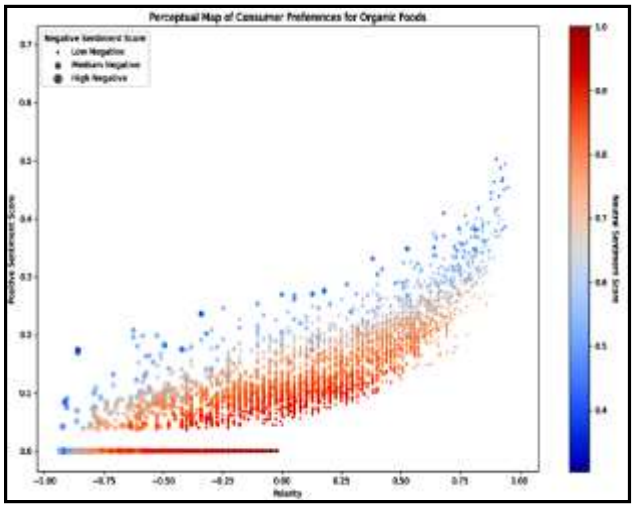

Figure 9: Sentiment Polarity and its Impact on Consumer Perception of Organic Foods.

The map illustrates a clear correlation between sentiment polarity and consumer perception of organic foods (see Figure 9). As polarity shifts from negative to positive, we observe a corresponding transition in sentiment from negative to positive. The cluster of red dots on the left, representing high negative sentiment, indicates a segment of consumers with unfavorable views of organic foods. Conversely, the blue dots on the right, signifying high positive sentiment, highlight a group with strongly positive perceptions. The gradual color shift from red to blue as polarity increases suggests a gradual transition in consumer sentiment, with neutral opinions lying somewhere in the middle. Notably, a larger cluster of data points with positive sentiment scores implies that most consumers have favorable opinions about organic foods. Additionally, the density of dots decreases as we move towards the extremes of polarity, suggesting that highly polarized opinions, whether positive or negative, are less frequent compared to more moderate views.

4.5. Cluster Modelling

The scatter plot visualizes clusters of organic food products based on their positive and negative sentiment scores derived from likely social media or online reviews (see Figure 10). A clear separation is seen between Cluster 0 (dark purple) and the dominant teal cluster. Cluster 0 products have shallow positive sentiment scores (close to 0) and a range of negative sentiment scores, indicating a largely negative perception. In contrast, the teal cluster showcases a wide range of positive and negative sentiment scores, suggesting a mixed reception among consumers. The negative sentiment distribution in the teal cluster shows that products gain less negativity when they score higher for positivity. Analysis of the map shows that Cluster 0 has negative perceptions of organic products, yet the teal cluster shows that the buyer's perspective matches reality more accurately.

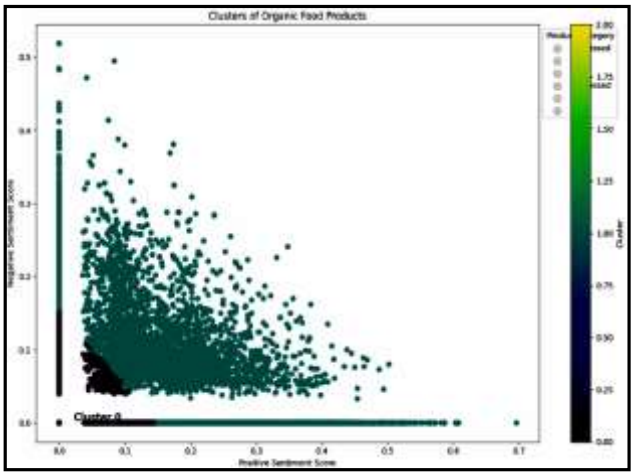

Figure 10: Clusters of Organic Food Products.

5. DISCUSSION

5.1. Implications of the Sentiment Analysis and Consumer Shifts

Consumer preferences have become more understandable post-pandemic through models including VADER, LSTM, and BERT, which better reveal sentiment polarity and tone. Analytic results show that consumers increasingly prioritize wellness, certification education, and naturally sourced products (Kour and Gupta, 2023; Joloudari et al., 2022). According to the Health Belief Model (HBM) (Valdez et al., 2020), perceived health advantages connected with lower risk exposure are key determinants influencing customer behavioural decisions. Manufacturers need to change their marketing approach by featuring the essential elements representing their target clientele's growing values (Rustam et al. 2021).

Consumers' positive views about the pandemic experience are outmatched by the continued importance of supply-chain disruptions and cost increases (Reshi et al. 2022; Aiyanyo et al. 2021). The Diffusion of Innovations (DOI) Theory explains these concerns by analysing cost barriers and accessibility issues (Darad and Krishnan 2023). Manufacturers

and retailers need to resolve consumer concerns to preserve trust levels and keep the market growing (Chandrasekaran et al. 2020).

Perceptual mapping and cluster modelling demonstrate a significant trend among millennials toward organic raw ingredients combined with semi-processed items because these consumers want easy to use while achieving health goals (Singh 2023). The DOI framework focuses on understanding how innovations fit into consumer lifestyle patterns. The development of new products must centre on broadening diverse offerings which cater to health-first and sustainability-developed consumer demands (Mishra et al. 2021; Katsafados et al. 2023).

5.2. Impact of COVID-19 on Organic Food Consumption

The COVID-19 pandemic has restructured customer habits, causing organic food recognition and adoption rates to soar dramatically (Chandra and Krishna 2021). The earlier market for organic items focused squarely on customers who combined wealth with health sensitivity status. The pandemic shifted market demand to include academic learners and professional and middle-aged professionals, extending beyond usual consumers (Jalil et al. 2022; Bengesi et al. 2023). The modified health belief model supports that increased awareness of disease risks drives people to replace unsafe food choices with healthier alternatives (Battula et al. 2022).

Analysis of global supply chain disruptions during the pandemic era reveals that food origin transparency proves essential for consumers (Singh et al. 2021). Consumer reassurance seeking in times of uncertainty has made organic products especially attractive due to their stringent safety and quality processes (Swapnarekha et al. 2023). The DOI framework shows that transparent and safe benefits accelerate technology adoption since Chandrasekaran and Saini (2021) demonstrated this principle.

5.3. Effectiveness of Machine Learning Models

Post-pandemic customer sentiment processing relies heavily on machine learning models to perform the essential analytics. The sentiment analysis tool VADER effectively examines large datasets through its ability to handle emoticons and slang (Pano and Kashef, 2020) when analyzing the 150,000 social media responses in this research. However, the system faces limitations when detecting sarcasm and complex situations, thereby reducing its effectiveness for detailed sentiment analysis (Yan and Liu 2022).

The LSTM model stands out due to its text dependency analysis capability, which makes it suitable for studying complex sentiment expressions (Behera et al. 2021). According to Tharu et al. (2023), LSTM models show superior performance to VADER models, particularly in situations demanding context-sensitive analyses.

The bidirectional attention mechanisms of BERT help users analyze delicate linguistic patterns, resulting in the most precise sentiment analysis (Cai et al. 2020). This model's exact analysis of complex reviews sharpens detailed insights, yet its resource-intensive nature could hinder implementation (Qorib et al. 2023).

When selecting a model to analyze subjective data, researchers should determine which model characteristics most closely align with their evaluation prerequisites. Combining these models establishes a comprehensive approach to consumer sentiment analysis, which guides organizational strategy in the organic food sector (Jijon-Vorbeck and Segura-Bedmar 2021).

5.4. Strategic Recommendations for Manufacturers

Manufacturers gain better market prediction skills in the post-COVID era while strengthening trust relationships with their customers. Manufacturers need to develop budget-friendly organic products to reach students and mid-income consumers according to research by Aiyanyo et al. (2021). Organic food advertisements featuring wellness characteristics attract young professional consumers who make health-related choices (Valdez et al. 2020). Supply chain resilience needs immediate attention since it minimizes organic product shortages and safeguards market confidence (Reshi et al. 2022). Organic companies can tap into new consumer segments by adding semi-processed and raw organic products as demand rises for accessible nutritious food choices (Singh 2023).

5.5. Implications for Future Research

The observations corroborate the call for more research to fully understand Consumer attitudes and behavior toward the organic food market. A more careful exploration of regional variations in consumer preferences may be another interesting topic for future research. In this study, global patterns are assessed, and the differences in cultural, economic, and environmental patterns per geographical region might have a rather mitigation impact on consumers' attitudes toward organic foods. This understanding could assist manufacturers in developing specific approaches to allowing consumers to satisfy their needs in specific

areas. Furthermore, identifying how regional policies and regulations affect the demand for organic foods could help develop guidelines for policymaking and the industry. Long-term, post-pandemic co, consumer behavior is not an area that needs to be explored. In any case, the pandemic has undoubtedly sped up some trends, although it is still unclear whether these trends will continue as before in the future. It is crucial to analyze trends that consumer behaviors have over several years through cross-sectional, as these studies could provide light on the sustainability of some identified trends. It can also analyze how the current factors affect the global consumption of organic foods, including climate changes and economic instabilities. This way, long-term behavior patterns help stakeholders gain better insight into what specific changes can be expected in the future and how stakeholders should adjust to them to maintain competitiveness in a market that is inevitably changing).

6. CONCLUSION

The study of the consumer's perception of organic foods after the pandemic cripple demonstrates essential changes within the two aspects under discussion: preferences and categorizations. Descriptor analysis exhibits relatively more positive sentiments emphasizing consumer consciousness of health, certification, and natural organic products. The pandemic contributed to the change in the audience for buying organic food, which includes young working people, students, and the middle-aged population. The findings trends have been validated by sentiment analysis models such as VADER, LSTM, and BERT, where BERT's nuanced understanding and technique of context analysis offered the most detailed view. Further, when using cluster modeling, a shift of customers' preferences to articles of semi-processed and raw organic food was established. This research is relevant in analyzing the organic food market in the post-pandemic period by using data from social media to obtain up-to-date consumer opinions. It stresses the usefulness of machine learning models in giving detailed insights about consumer sentiments and the micro-level trends prevailing in the market. Some common conclusions that can be drawn: Marketing messages should be changed according to market trends and the growing popularity of products with references to their healthy properties and the environmental impact of production. The paper offers valuable information for manufacturers to understand the potential buyers and main categories of organic foods in the new market environment.

6.1. Study Limitations

This study primarily focuses on understanding post-COVID-19 consumer preferences towards organic foods, drawing from 150,000 social media responses collected between January 2020 and December 2023. While this data provides valuable insights into changes in consumer perceptions, the use of social media data may introduce biases, as it reflects the opinions of active users rather than the general population. Despite these limitations, the chosen scope allows for a detailed analysis of the modern consumer profile and its implications for the organic food market.

Acknowledgements: We acknowledge BML Munjal University (BMU), Gurugram, for its valuable support and resources, which significantly enabled the completion of this research.

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