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Sentiment analysis of online user comments on artificial meat

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ABSTRACT

Artificial meat is a sustainable protein source that has riveted attention recently. However, differences of opinion have led to the need for more research on the issue. The controversy complicates the assessment of whether or not artificial meat will potentially be consumed in the future. This study aimed to determine the emotional states of YouTube users toward artificial meat. For this purpose, YouTube was used as a considerable data source in determining individuals' emotions and opinions. User comments on popular videos about "artificial meat" shared on online were evaluated using sentiment analysis (SA). They were classified as positive, neutral, and negative according to their polarity scores in the lexicon-based SA method. Analysis results demonstrated that 11,113 (40.8%) of the user comments were positive, 9,054 (33.2%) were negative, and 7,064 (25.9%) were neutral. The most frequently repeated words were "meat, eat and like" while the most frequent negative words were "fake, cancer, synthetic and expensive" respectively.

Keywords:
Artificial Meat,
User Opinions,
Sentiment Analysis,
Natural Language Processing,
Online Comments.

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1. Introduction

Sustained growth in world population, incomes, and urbanization has significantly increased the demand for meat products (OECD-FAO, 2013). Global meat consumption is expected to be 49 kg per capita on average in 2050. This value corresponds to a 40% increase compared to the 2018 total production amount (De Souza-Vilela, Andrew & Ruhnke, 2019). The demand for meat is, in turn, increasing rapidly, widening the gap between demand and supply (Shan et al., 2022). For these reasons, artificial meat has been suggested as an innovative alternative to traditional meat and a sustainable protein source (Asioli et al., 2022). Artificial meat is described as the product obtained by transforming the stem cells of the animals raised for food purposes into edible mature muscle cells first and then into larger muscle tissues in a laboratory environment (Dupont & Fiebelkorn, 2020). It is also known as "in vitro meat," "clean-synthetic meat," and "cultured meat" (Mancini & Antonioli, 2019). The first artificial meat was produced by the Russian Institute of Experimental Veterinary Medicine in 2017. The world's first artificial meat-based burger was produced in the laboratory of Dr. Mark Post at Maastricht University in the Netherlands for $325,000 (Farhoomand, Okay, Aras & Büyük, 2022). Artificial meat production has begun by companies such as Memphis Meat (San Francisco, California), Super Meat (Israel) and Mosa Meat (Netherlands). The Singapore Food Agency (SFA) gave regulatory approval to startup Eat Just Inc. to sell lab-grown chicken meat in late 2020. It became the first government in the world to allow the commercialization of cultured meat. Artificial meat will officially become part of the U.S. food system in 2023. Manufacturers such as UPSIDE Foods and Good Meat have received approval to commercialize cell-cultured chicken meat nationwide (Good Meat, 2023; UPSIDE Foods, 2023; Da Silva & Conte- Junior, 2024).

Despite its endorsement by many people for its potential environmental and climate benefits, artificial meat also raises suspicion and criticism (Bhat et al., 2015). For this reason, artificial meat and public perceptions is an emerging research topic (M. Zhang, Li & Bai, 2020). Various studies have cited the advantages and disadvantages of artificial meat. Its benefits included enabling mass production with limited natural resources by protecting soil and water resources (Post, 2012), ensuring animal welfare (Hocquette, 2016; Mariasegaram et al., 2012), reducing the carbon footprint in the laboratory and relieving the pressure on the environment (Gilbert, 2010), reducing the risk of animal-borne diseases (e.g., mad cow and foot-and-mouth disease) and food safety concerns, and being a clean source of protein (Bonny et al., 2015), being a sustainable alternative protein source in times of famine (Shen & Chen, 2020), and having customizable ingredients according to different nutritional demands (Mateti et al.,, 2022). Its unhealthiness, price, taste, color, texture, shelf life, and cultural, ethical, religious, and social factors were cited as potential pitfalls (Goodwin & Shoulders, 2013;

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Ünver Alçay et al., 2018; M. Zhang et al., 2020; Welin, 2013). Conspiracy theories, fears, phobias, disgust sensitivity, general world views, conservatism, naturalism, and scientific distrust were also added to the list of drawbacks of artificial meat (Siddiqui et al., 2022). However, the prevalent negative emotion about artificial meat stems from its being unnatural (L. Zhang et al., 2021).

Opinions about artificial meat are divided into two opposing poles among scientists, society, and research (Bryant & Barnett, 2020; Dupont & Fiebelkorn, 2020; Slade, 2018; Mancini & Antonioli, 2019; Wilks & Phillips, 2017). For instance, advocates of artificial meat claim that greenhouse gas emissions and land and water use will be reduced twice compared to traditional production. However, opponents believe it will not bring a real advantage since it will lead to a limited reduction in fossil fuels and water use and a rise in land area (Hocquette, 2016). These arguments becloud the evaluation of whether artificial meat is potentially “consumable” or “unconsumable” in the future. Differences of opinion on artificial meat have thus created the need for more research on the issue. Consumer acceptance is critical to the success of artificial meat (Pakseresht et al., 2022). Haagsman et al., (2009) also underlined that “consumer acceptance” was crucial. Sustainable purchasing and consumption of artificial meat requires workable solutions (Liu et al., 2022). In this context, it is essential to understand the current public perceptions of artificial meat to identify long-term strategic plans (Laestadius & Caldwell, 2015).

Previous studies tackled artificial meat in terms of willingness to try (WTT), willingness to buy (WTB), willingness to pay (WTP), advantages-disadvantages, and critical perspective (Asioli et al., 2022; Bryant & Barnett, 2020; M. Zhang, Li & Bai, 2020; Mateti et al., 2022). Therefore, the studies fail to reveal whether artificial meat will be accepted by society in general. To this end, this study aimed to understand the public opinions on artificial meat.

In this regard, comments on online news videos were analyzed. Online comments can be considered a “reflection of the pulse of society.” (Loke, 2013). Additionally, online comments alone might influence public perceptions (Poria & Oppewal, 2003). In this regard, it is crucial to understand the opinions from online comments to determine the prospective pulse of artificial meat. Online comments have been available as a valuable source of public opinion, with many studies now utilizing analysis of online comments (Brossoie et al., 2012). In addition, unlike quantitative and qualitative methods, users are more likely to express their honest opinions on a topic, as they do this voluntarily, without prejudice.

To our humble knowledge, no study evaluated online user comments on artificial meat and revealed their emotional states. In this context, understanding the general public opinions about the prospective consumption of artificial meat is essential. This study specifically aimed to fill this gap.

2. Literature Review

Lexicon-based sentiment analysis

SA was first used by Tetsuya and Jeonghee (Tetsuya & Jeonghee, 2003) and opinion mining was pioneered by Kushal et al. (2003). It is a current research field aimed at determining subjective information, such as emotions, opinions, and attitudes of opinion holders in texts through specific methods and techniques in natural language processing (NLP), statistics, computer science, etc. (Ravi & Ravi, 2015). It aims to reveal whether individuals’ emotions and opinions about a phenomenon are positive, negative, or neutral through computer science (Wilson, Wiebe & Hoffmann, 2005). In this sense, individuals might have different factors (persons, issues, objects, or entities) on which they comment.

SA is generally handled at three different levels: “document-level,” “sentence-level,” and “aspect-based or feature-based.” In document-level SA, opinion-expressed articles are holisticaly evaluated to reveal the emotional polarity in the text. One of the challenges experienced at this level arises when more than one opinion is included in the document. Unlike document-level SA, texts are not holistically classified, but all sentences within the text are examined and defined as objective or subjective in sentence-level SA. This level is widely used in Web 2.0 systems to analyze the opinions in the data in social media environments created by users as producers/consumers. In feature-based SA, information about the emotional states of the text and the commented feature can be obtained through feature extraction processes. A case where a customer has both positive and negative comments about any product can be an example of this level (Boudad et al., 2017; Jagtap & Pawar, 2013; Medhat, Hassan & Korashy, 2014; Özyurt & Akcayol, 2018; Shirsat et al., 2017).

Lexicon-based methods in SA aim to analyze emotions through lexical items comprising emotive words or phrases. Therefore, calculations are made based on the semantic orientations of the words and sentences in the texts. Word-based methods are divided into two: corpus-based approaches and dictionary-based approaches. In the word-based method, antonyms and synonyms are found using words, such as a manually created set of emotive words (WordNet), with the set expanded and the search terminated when no new words are found. In the corpus-based method, statistical or semantic methods are employed to determine the polarity of opinions (Machová & Marhefka, 2013; Turney, 2002; Yousef et al., 2014).

Emotions are the fundamental elements that create the value hidden in the content produced and circulated by social media users. In addition to videos, photos, music, and messages, these emotions can be expressed through emojis and likes. Therefore, it is crucial to analyze or

Table 1: Titles, URLs, and number of comments of the analyzed YouTube news videos

News Titles and URLs (Foreign)	Total Number of Comments	Number of Top Comments	News Channel
1.Lab-Grown Meat is Here… and I Taste-Tested It!- 27 Jun 2023 Url: https://www.youtube.com/watch?v=08nHuUbt8SQ	3.545	2690	Be Smart
2. What Is Synthetic Meat? - 21 Feb 2021 Url: https://www.youtube.com/watch?v=Ktgh51E8V1Q	1.503	1122	Dr. Eric Berg DC YouTube Channel
3. I Tried Cultured Meat: Is It The Future of Food?-1 Apr 2023 Url: https://www.youtube.com/watch?v=aFLV60CJNho	509	200	CNET
4. Can Lab-Grown Steak be the Future of Meat? | Big Business | Business Insider- 17 Jul 2022 Url: https://www.youtube.com/watch?v=UQejwvnog0M	3.587	2123	Insider Business YouTube Channel
5. Lab Meat. The $1 Trillion Ugly Truth- 15 May 2023 Url: https://www.youtube.com/watch?v=V0zCf4Yup34	3.737	2155	What I've Learned YouTube Channel
6. The Future of Meat - Lab Grown Meat Explained-10 Aug 2021 Url: https://www.youtube.com/watch?v=hVBq4Pw2_fQ	3.112	1987	Undecided with Matt Ferrell YouTube Channel
7. The Meat of the Future: How Lab-Grown Meat Is Made- 2 Oct 2015 Url: https://www.youtube.com/watch?v=u468xY1T8fw	821	380	Eater YouTube Channel
8. The Truth About Lab-Grown Meat- 27 Nov 2021 Url: https://www.youtube.com/watch?v=DmanbWwMa5w	2.048	1154	Real Science
9. You might be eating Bill Gates lab grown meat tonight | Redacted with Clayton Morris-1 Tem 2023 Url: https://www.youtube.com/watch?v=0iUWtLSRlDc	3.636	2658	Redacted YouTube Channel
10. Tasting the World's First Test-Tube Steak- 11 Dec 2018 Url: https://www.youtube.com/watch?v=bjSe-0vSRMY	15.361	8293	Wall Street Journal YouTube Channel
11. Dining at The World's Largest Synthetic Meat Factory-24 Nov 2021 Url: https://www.youtube.com/watch?v=KSS9Em4a_qs	666	417	Bloomberg Originals YouTube Channel
12. Lab-grown chicken approved for sale in US | GMA-22 Jun 2023 Url: https://www.youtube.com/watch?v=XdkskowAHkY	502	320	ABC NEWS
13. Inside the Quest to Make Lab Grown Meat | WIRED- 16 Feb 2018 Url: https://www.youtube.com/watch?v=QO9SS1NS6MM	3.197	1833	WIRED YouTube Channel
14. Lab grown meat is literally a scam- 10 Aug 2023 Url. https://www.youtube.com/watch?v=myX1uav1Kxk	3.367	2097	Evil Food Supply YouTube Channel
15. Lab-Grown Chicken Can Now Be Sold in the U.S.- 21 Jun 2023 Url: https://www.youtube.com/watch?app=desktop&v=c-WPHIuPmug	535	199	Time YouTube Channel
Total Number of Comments	**46.126**	**27628**	

Source: By the author

interpret emotional states in social media environments automatically or semi-automatically. In particular, content shared profusely by social media users (Varma et al., 2017) constitutes the primary data source for SA. In connection with this, research on analyzing social media content has increased significantly in recent years, with many methods proposed for SA. Among the recommended methods, Valence Aware Dictionary for Sentiment Reasoning (VADER), a simple rule-based model developed by Hutto and Gilbert (2014) and giving the most reliable results, was employed in this study. VADER was compared with 11 algorithms: machine learning-focused methods (e.g., LIWC, Naive Bayes (NB), Support Vector Machines Regression (SWM-R), Support Vector Machines Classification (SWR-C), Maximum Entropy (ME) and lexicon-based methods (e.g., LIWC, GI, Hu-Liu04, and ANEW). The comparative results revealed that it was the best-performing algorithm with 0.96 and 0.84 classification accuracy in evaluating emotions in social media texts.

3. Method

The study evaluated user comments on the videos about "artificial meat" on YouTube, one of the social media platforms, through SA. This section includes the data set, data collection, pre- processing, and sentiment analysis.

Data set

Within the scope of the study, user comments on YouTube were analyzed through an NLP- based SA method. YouTube is a comprehensive source of video information where videos are real- timely uploaded. It is one of the largest video-sharing platforms in the world among online social media platforms such as Facebook, Twitter, and Google+ (Bhuiyan et al., 2017). It is also the second most popular web search engine (Amarasekara & Grant, 2019). Additionally, it is crucial for the scientific community concerning the provision of information transfer and a data source for researchers thanks to likes, views, and comments (Alhujaili & Yafooz, 2021; Amarasekara & Grant, 2019). NLP-based comment analysis is a low-cost method to evaluate public emotions (Singh & Tiwari, 2021). Accordingly, this gradually adds to the significance of YouTube for the sector and the research community. However, research on establishing trends from these comments has been scarce despite the significant number of user comments and reviews on most of these videos (Singh & Tiwari, 2021). The top 15 videos with the most comments selected by typing "artificial meat" on YouTube

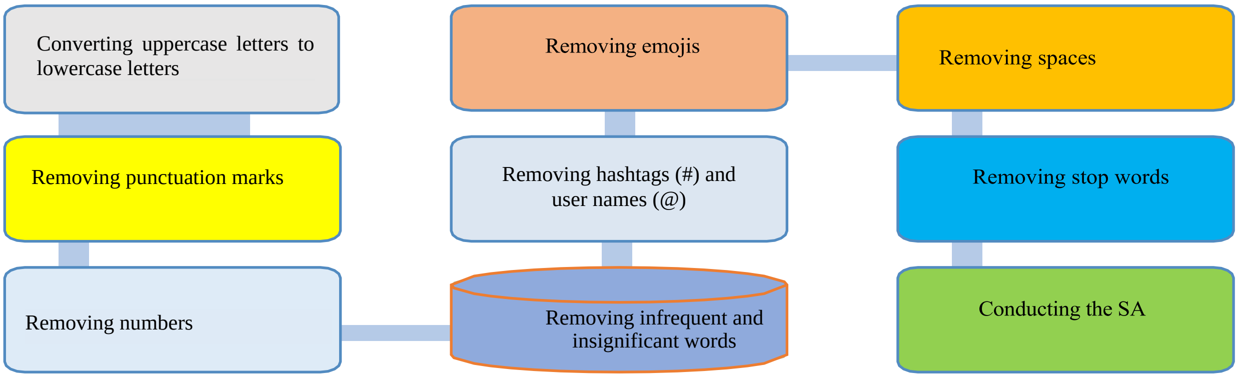


Figure 1. Data pre-processing steps

Source: By the author

constituted the data set of this study. The resulting data set included sentiment analysis of the comments on the published videos. The data set is based on top comments[1]. on YouTube on September 24, 2023. YouTube videos within the data set and the number of top user comments on these videos are displayed in Table 1.

Data Pre-processing and Text Mining

The study was conducted through a lexicon-based method. Successfully analyzing English words, the VADER lexicon algorithm was employed in lexicon-based SA. A pilot group was selected to determine the success rate of the VADER lexicon algorithm in the acquired data set. The sentiment results coded by the VADER algorithm and researchers for each comment were compared using the data set of the pilot group. Results indicated an 81.24% success rate of the lexicon-based VADER algorithm in determining emotional states.

YouTube video comments were used as raw data sources in the SA. The public comments (n=27,628) under the YouTube videos were extracted using the MAXQDA qualitative data analysis program and transferred into an Excel file. Within the scope of the study, text mining pre-processing steps were executed on the comments in the Excel file using the Python software language "Google Colab."

During pre-processing, the data cleansing step was initiated. The codes and steps used for the data cleansing are given in Figure 1. Developed by Guido Van Rossum in the early 1990s, Python was preferred because it contains comprehensive libraries for machine learning and data analysis/processing and is easy to use. Google Colab, or "Colaboratory," is a programming platform that enables Python to be written and run without any configurations via the browser, with free access to GPUs and easy sharing (Dierbach, 2012).

The libraries utilized in the study were pandas, numpy, nltk, demoji, and matplotlib.

➢Step 1- Reading the data: Pandas is a library that allows easy processing of files with csv and .txt extensions. The words and their frequencies on YouTube were identified using the Pandas library.

➢Step 2- Organizing the data: In NumPy, the features used in the data set are assigned to variables as columns, and each created variable is used to dimension the sentiment values with the NumPy library.

➢Step 3- Describing the libraries: NLTK is a platform for creating Python programs working with human language data. With easy-to-use interfaces for over 50 companies and textual resources, such as WordNet, it is a set of text-processing libraries for classification, identification, sourcing, tagging, parsing, and semantic reasoning.

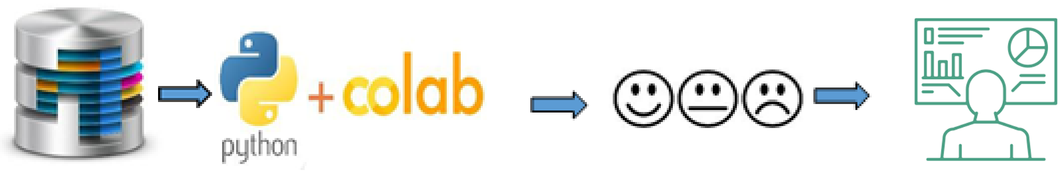
➢Step 4- Preliminary data preparation: Demoji are facial expressions used to express emotions.

Emojis were detected and removed from the data set.

Data classification and sentiment analysis

After data pre-processing, SA was conducted using the VADER, one of the popular libraries of NLP. The VADER system offers four outputs: positive, negative, neutral, and composite values. Positive, negative, and neutral values indicate how positive, negative, and neutral that text is (B. Aslan & Erdur, 2020). Composite value is a total score value that includes positive, negative, and neutral values. The degree of positivity/negativity is presented between [−1, +1]. -1 indicates proximity to negativity, and +1 indicates an increase in the positivity of the sentence (Demir et al., 2020). Indeed, the specific threshold values used to classify YouTube user comments as positive, negative, or neutral through VADER were as follows: "Fpi = positive vs >= 0.05 / $negative$ vs <= −0.05 / neutral otherwise"[2] (Hutto & Gilbert, 2014; S. Aslan, 2023). Upon the value-based SA, the composite value was classified as positive if equal to or greater than [+.05], negative if smaller than or equal to [-.05], and neutral if between

[1] *Primary comments on the videos were taken as a basis. Replies to comments by other users were excluded.*
[1] *In the value, vs represents the combined score of the i. comment, with Fpi indicating the sentimental polarity of the i. comment. After identifying the emotional states of the comments in the data set, the study focused on comments with positive, negative, and neutral emotional states.*



Data Set **Data Pre-processing** **Sentiment Analysis** **Visualization**

Figure 2. Sentiment Analysis Model

Source: *By the author*

[+.05] and [-.05]. classified as positive if equal to or greater than [+.05], negative if smaller than or equal to [-.05], and neutral if between [+.05] and [-.05].

As shown in the SA model in Figure 2, the data were divided into positive, negative, and neutral in the sentiment classification stage. The Matplotlib library was used to visualize the SA's positive, negative, and neutral findings. SA results about the topic discussed within the scope of the study are presented under the findings section.

4. Findings

The study comprised a data set of 27,628 user comments about artificial meat on YouTube videos. After pre-processing the collected data set (Figure 3), 27,231 user comments were collected in three different sentiment categories: positive, negative, and neutral. The number and percentage distributions of the data sentiment classification are given in Figure 3.

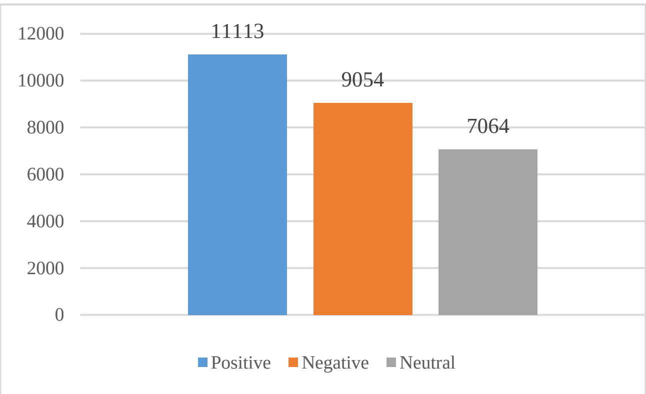


Figure 3. Sentiment States of Posts

Source: By the author

Figure 3 shows the emotional states of user comments on video posts about artificial meat on YouTube, one of the social media platforms. It was concluded that 40.8% of the user comments on artificial meat videos (11,113) were positive, 33.2% (9,054) were negative, and 25.9% (7,064) were neutral. The study sample revealed that YouTube users' emotions toward artificial meat videos were predominantly positive, while the negative and neutral emotions were equally distributed.

Appendix 1indicates the user comments, SA scores, and tags of YouTube videos about artificial meat. Based on the sample user comments selected from the data set, it is manifest that any user comments with uncertainty regarding the emotional states or containing interrogative expressions are assigned a neutral label by specifying the polarity score as "0." The scores of other user comments emerge after calculating the words in positive or negative sentences.

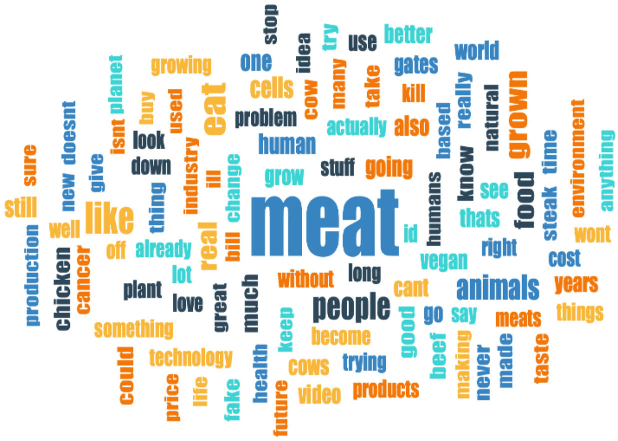


Figure 4. Word Cloud of Comments on Artificial Meat

Source: *By the author*

Word clouds were formed to visualize the data set handled in the study. By measuring the frequency levels of the high-frequency words in the text, they provide a general overview and assist with the interpretation within a specific context (Heımerl et al., 2014). A visual word cloud was created from user comments on YouTube videos about artificial meat. As seen in Figure 3, the words in user comments are shaped according to color and size. High-frequency words are illustrated as dark and large, and low-frequency words are shown as light and small in this cloud (Yaşa, 2022). The word cloud indicates that the most frequent word was "meat," followed by "eat, like, grown, people, food, animals, real, make, cells," respectively. The frequency and percentage distributions of these words are given in Table 3.

Table 3. Top 10 Word Frequencies and Percentages in Comments about Artificial Meat

Total Word Count =318170	Frequency	%
Meat	11372	3,57
Eat	3439	1,08
Like	3420	1,07
Grown	2512	0,79
People	2445	0,77
Food	1952	0,61
Animals	1929	0,61
Real	1721	0,54
Cells	1255	0,39
Chicken	1118	0,35

Source: *By the author*

The total number of words in user comments on the research topic was 490392. The analysis of the frequency and percentage distributions of the most frequent words in 27231 user comments on YouTube videos revealed the following: “meat” n=11372 (%3,57), “eat” n=3439 (%1,08), “like” n=3420 (%1,07), “grown” n=2512 (%0,79), “people” n=2445 (%0,77), “food” n=1952 (%0,61), “animals” n=1929 (%0,61), “real” n=1721 (%0,54), “cells” n=1255 (%0,39) and “chicken” n=1118 (%0,35). Since the research topic was about artificial meat, it is predictable that the most frequently used word was “meat,” with other high-frequency words also supporting the research topic.

Table 4. Top 10 Negative Word Frequencies and Percentages in Comments on Artificial Meat

Total Word Count =318170	Frequency	%
Fake	1113	0,27
Cancer	912	0,22
Synthetic	505	0,12
Expensive	453	0,11
Wrong	297	0,07
Sick	270	0,07
Evil	266	0,07
Disgusting	231	0,06
Worse	213	0,05
Poison	154	0,04

Source: *By the author*

The analysis of the frequency and percentage distributions of the most frequently mentioned negative words in 27231 user comments on YouTube videos revealed the following: “fake” n=11372 (%0,27), “cancer” n=912 (%0,22), “synthetic” n=505 (%0,12), “expensive” n=453 (%0,11), “wrong” n=297 (%0,07), “sick” n=270 (%0,07), “evil” n=266 (%0,07), “disgusting” n=231 (%0,06), “worse” n=213 (%0,05), and “poison” n=154 (%0,04).

5. Conclusion and Discussion

Although the idea of artificial meat production has been around for a long time, it has gained importance in recent years in parallel with technological developments. Artificial meat is among the leading issues recently discussed as innovative approaches in gastronomy. Referred to as the alternative protein source of the future, artificial meat was handled critically in some studies. Current debates and studies in the literature complicate the evaluation of whether artificial meat will potentially be consumed in the future. Differences of opinion about artificial meat have raised the question of what consumers think about this issue. In this context, determining the current public perceptions to determine the long-term strategic plans for artificial meat contributes to the significance of the study.

Findings indicated that 11,113 (40.8%) of the user comments were positive, 9,054 (33.2%) were negative, and 7,064 (25.9%) were neutral. Although positive opinions were generally higher than negative ones, the proportion remained below 50%. Despite the small proportion, it predominantly indicates the possibility that individuals might prefer artificial meat over traditional meat or other alternatives. The most frequently used words in the findings, such as “meat, eat, like, and real,” also lend support to the prevalence of positive opinions. Marketing strategies can thus focus on themes containing the most frequently used positive word groups, such as “eat, like, and real.” Despite the search for videos using “artificial meat” as the query item, the word “artificial” was not included among the top ten words in the comments, supporting the finding that comments were weighted positively.

Top online comments might alone influence public perceptions (Poria & Oppewal, 2003). The high number of positive comments within the scope of the study might, therefore, encourage users who made neutral (25.9%) comments to hold a generally positive perception of artificial meat. The most frequent negative words in comments about artificial meat were “fake,” “cancer,” “synthetic,” and “expensive”. Users’ negative comments about artificial meat stemmed from its being unnatural (fake, synthetic). The result of this study supports a previous study (L. Zhang et al., 2021). In a qualitative study conducted by Verbeke et al., (2015), it was found that the participants' first negative feelings about artificial meat were due to disgust and unnaturalness. In the study conducted by Laestadius and Caldwell (2015) using the online comment analysis method, positive comments about artificial meat were mostly related to animal welfare, environmental and public health benefits, while negative comments were about cultured meat being unnatural and unattractive.

The idea that artificial meat might cause cancer was another reason for negative comments about the topic. Consumers fear that since it is a new technology, the long-term health effects of consuming artificial meat products on humans are unknown and may be harmful to health. Another issue that causes consumers to have negative feelings about artificial meat is that it is expensive. The results of this study are similar to the finding in the study conducted by Baran (2020) that consumers wanted to pay less for cultured meat compared to normal meat. In the study conducted by Choudhury et al., (2020), it was determined that the price barrier had an impact on artificial meat preference. In this context, it is estimated that artificial meat consumption will become widespread, largely due to overcoming the price barrier against traditional meat. It is recommended that the reasons for negative consumer opinions should be prioritized in identifying long-term strategic plans on the topic

In the future, artificial meats, which are meat alternatives, will be available in the food and beverage industry and in markets, and it is expected that there will be strong competition between them. As a matter of fact, there are plant-based meat alternatives that are accessible and consumer acceptable in the market (Hoek et al., 2011). It is thought that positive consumer opinions about artificial meat will increase the competitive potential of restaurants. It is estimated that artificial meat may become an important competitive element in restaurant menus and markets in the coming years, especially for consumers who are willing to reduce their meat consumption. However, consumers expect to pay less money because they believe that artificial meat will be a more artificial product than traditional meat.

Future studies examining differences in emotional responses based on factors such as age, gender, and geographic location could help better understand social perceptions of artificial meat.. Conducting more extensive surveys and focus group studies can assess people's emotional reactions and thoughts about artificial meat in more detail. These studies can supplement quantitative results with qualitative data collection methods and provide deeper understanding. Additionally, the emotional analysis of people who adopt a vegan diet could be a special research topic.

Strengths and limitations of the study

SA research began in the early 2000s and is a quick and low-cost method of online opinion analysis this method utilizes online opinion sources (e.g., Twitter, YouTube, etc.). Since online opinion sources might alone impact public perceptions, determining the emotional states toward an issue is also significant for sector managers. The emotional intensity specified through the SA method contributes significantly to predicting sales trends, identifying opinions about the product, and developing marketing strategies. The method used in the study is considered salient in that it was demonstrated that consumer opinions might be determined easily and cost-effectively on newly launched gastronomical products. Another strength of the study was that commenters might present honest opinions on the topic voluntarily, without prejudice, unlike qualitative and quantitative methods. The high number of consumer opinions (27,231) in the data set was another strength of the study.

The study suggests that intercultural differences might play a significant role in accepting artificial meat by consumers. Therefore, the failure to generalize the results constitutes the study’s limitation. Prospective studies might focus on the emotional intensity of consumers from different nationalities, languages, and regions. The obtained results might be evaluated comparatively.

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APPENDIES

Appendix 1: User Comment Examples, Scores, and Tags of YouTube Videos about Artificial Meat

User Comments	SA Scores	Tags
brilliant idea long genuinely safe consume big step helping whole world love hope takes off	{'neg': 0.0, 'neu': 0.385, 'pos': 0.615, 'compound': 0.9432}	Positive
finally Buddhist vegetarian eat milk cause can't make killing living creature excuse	{'neg': 0.0, 'neu': 0.675, 'pos': 0.325, 'compound': 0.5881}	Positive
I've hearing years want taste clean meat asap	{'neg': 0.0, 'neu': 0.6, 'pos': 0.4, 'compound': 0.4588}	Positive
meat isn't murder anymore vegans get normal instead eating copycat meals	{'neg': 0.0, 'neu': 0.728, 'pos': 0.272, 'compound': 0.5773}	Positive
love meat but I'd rather not kill animals eat would love lab grown meat saving much energy	{'neg': 0.0, 'neu': 0.446, 'pos': 0.554, 'compound': 0.9528}	Positive
years later study shows if eat lab grown food higher chance getting cancer	{'neg': 0.253, 'neu': 0.632, 'pos': 0.115, 'compound': -0.5267}	Negative
I'd rather cow killed eat real meat problem lab grown things don't know could putting without telling also could start getting imported countries like china producing fake fake meat would hard tell difference real fake meat vs fake fake meat long story short if ain't broke don't fix	{'neg': 0.36, 'neu': 0.568, 'pos': 0.072, 'compound': -0.9599}	Negative
will cause cancer	{'neg': 0.688, 'neu': 0.312, 'pos': 0.0, 'compound': -0.6597}	Negative
shittiest idea i've seen like times cheaper slaughter cow sell meat instead going lab process can't let cows live will eventually repopulate much will start killing	{'neg': 0.257, 'neu': 0.671, 'pos': 0.073, 'compound': -0.8074}	Negative
lab grown meat harmful humans regular meat therefore not ethical company personally won't buying products	{'neg': 0.162, 'neu': 0.838, 'pos': 0.0, 'compound': -0.4023}	Negative
check mate vegans still real meat	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral
would vegans eat	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral
would vegans take bite	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral
would someone waste time making fake meat	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral
tissue stem cells harvested cow	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	Neutral

Source: *By the author*

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INFO PAGE

Sentiment analysis of online user comments on artificial meat

Abstract

Artificial meat is a sustainable protein source that has riveted attention recently. However, differences of opinion have led to the need for more research on the issue. The controversy complicates the assessment of whether or not artificial meat will potentially be consumed in the future. This study aimed to determine the emotional states of YouTube users toward artificial meat. For this purpose, YouTube was used as a considerable data source in determining individuals' emotions and opinions. User comments on popular videos about "artificial meat" shared on online were evaluated using sentiment analysis (SA). They were classified as positive, neutral, and negative according to their polarity scores in the lexicon-based SA method. Analysis results demonstrated that 11,113 (40.8%) of the user comments were positive, 9,054 (33.2%) were negative, and 7,064 (25.9%) were neutral. The most frequently repeated words were "meat, eat and like" while the most frequent negative words were "fake, cancer, synthetic and expensive" respectively.

Keywords: *Artificial Meat, User Opinions, Sentiment Analysis, Natural Language Processing, Online Comments.*

Authors

Full Name	Author contribution roles	Contribution rate
Merve Onur:	*Conceptualism, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing*	*100%*

Author statement: *Author(s) declare(s) that All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.* ***Declaration of Conflicting Interests:*** *The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article*

This paper does not required ethics committee report

Justification: The methodology of this study does not require an ethics committee report.