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Exploring public perceptions of precision fermentation technology: A streamlined and labor-saving consumer perception analysis approach using YouTube data

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ABSTRACT

This study investigates public perceptions of precision fermentation technology using an efficient, scalable analysis framework based on YouTube data. Leveraging the YouTube API for data collection and applying BERTopic for topic modelling and GPT-4o for sentiment analysis, we analysed 345 videos and 16,428 audience comments. Our results show that content creators largely portray precision fermentation positively, emphasizing innovation, sustainability, and alternative protein potential, while audience sentiment is more sceptical, reflecting a nuanced divergence in public attitudes. To unpack the reasons behind this divergence in sentiment, we applied topic modelling, which revealed a range of recurring public concerns and thematic patterns in the discourse. Overall, this analysis approach provides quick, data-driven insights into public perceptions and is adaptable to other sustainable food innovations, offering a practical tool for researchers and organisations to inform strategic decisions and facilitate the broader adoption of emerging food technologies.

1. Introduction

Precision fermentation is reshaping the global food industry, offering a sustainable and innovative solution to pressing challenges such as climate change and ethical concerns surrounding traditional agriculture (Kossmann et al., 2023). By harnessing genetically engineered microorganisms to produce specific compounds such as proteins and enzymes, this technology enables the creation of animal-free alternatives like dairy proteins and meat components, and it has the potential to transform consumer diets, aligning with the growing demand for sustainability and ethical food choices (Hilgendorf et al., 2024).

With companies like Perfect Day already commercialising precision-fermented products such as ice cream, cheese, and milk (Fytsilis et al., 2024; Waltz, 2022), the industry is advancing rapidly. However, the success of these innovations hinges not only on their technical or environmental merits but also on their societal acceptance (Chen et al., 2024; Kühl et al., 2024). Consumer perceptions, shaped by factors like trust, safety, naturalness, and personal values, are known to significantly influence the market adoption of novel food technologies (Muiruri and Rickertsen, 2024; McCluskey et al., 2016; Cai et al., 2024; Ulaga and Chacour, 2001).

Previous studies have explored public attitudes toward alternative proteins and food tech innovations, such as cultured meat and gene-edited crops, often relying on survey methods and controlled experiments (Bryant and Barnett, 2019; Kühl et al., 2024; Siegrist et al., 2018). While valuable, these approaches are often time-limited, lack spontaneity, and may not capture organically expressed sentiment across diverse demographics. As a result, researchers are increasingly turning to social media platforms to capture more dynamic and large-scale representations of public opinion (Feldmeyer and Johnson, 2022; Molenaar et al., 2024).

YouTube, in particular, offers a rich and underutilised source of public discourse. It not only hosts publisher-generated content but also facilitates direct viewer responses through comments and engagement metrics (Alhujaili and Yafooz, 2021; Bhuiyan et al., 2017). Prior studies have shown that YouTube comments can reflect public sentiment, value orientations, and trust dynamics around food innovations and sustainability topics (Teng et al., 2020; Tsiourlini et al., 2024). While the content is influenced by creators, viewer interactions provide a valuable lens into audience reactions, concerns, and acceptance patterns, making YouTube a suitable medium for perception analysis (Ghosh and Tripathi, 2025). Through video transcripts and comment sections, YouTube offers

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a rich dataset for analysing how precision fermentation and its products are presented, discussed, and received by a broad audience. It not only reflects consumer sentiment but also highlights the role of content creators in shaping narratives and influencing public opinion. Analysing these interactions allows researchers to uncover the societal factors affecting the acceptance and adoption of these novel food technologies.

Despite the growing importance of public perception in food tech adoption, little research has examined how precision fermentation is discussed and received in public online spaces. This study addresses that gap by applying a natural language processing framework to analyse YouTube video transcripts and associated audience comments. Using BERTopic for topic modelling and GPT-4o for sentiment analysis, the study captures both thematic and emotional dimensions of public discourse surrounding precision fermentation. Topic modelling identifies key themes within public discourse, while sentiment analysis captures the emotional tone of discussions, offering a comprehensive understanding of public attitudes (Rachel J et al., 2024; Singgalen, 2022). By addressing critical questions, such as "What sentiments are expressed about precision fermentation and its products?" and "What themes dominate discussions around these innovations?", this study extends previous research by offering a scalable, data-driven method to assess societal reception of food technologies. It contributes to both academic understanding and practical tools for organisations seeking to track and respond to consumer sentiment in real time.

2. Background and related work

Precision fermentation offers clear sustainability and ethical advantages, it also raises a number of concerns that may contribute to public scepticism. For some consumers, the use of genetically modified microorganisms and lab-based production processes may evoke fears around unnaturalness, food safety, or loss of traditional farming practices (Bryant and Barnett, 2019; Siegrist and Hartmann, 2020). Others may question the long-term health effects of consuming precision-fermented proteins, particularly in the absence of long-standing safety records. Additionally, there are concerns about transparency in labelling, corporate ownership of food systems, and potential greenwashing by companies promoting novel technologies (Banovic et al., 2025; Yamaguchi et al., 2024). Ethical debates around the role of biotechnology in food production further complicate consumer acceptance. These issues, while sometimes lacking scientific grounding, can powerfully shape public sentiment.

In response to such concerns, researchers have increasingly sought to understand how consumers perceive emerging food technologies, including precision fermentation. Recent food science research has provided significant insights into these dynamics. Products like plant-based and cultured meat have been extensively studied for consumer perception and opinions using survey-based methods (Appiani et al., 2025; Nautiyal and Lal, 2025; Chen et al., 2024; Tsvakirai et al., 2024; Song et al., 2024; Kühl et al., 2024). These approaches have significantly advanced the understanding of consumer attitudes in food innovations. However, they often require extensive manual effort and time, limiting the scalability and ability to capture real-time consumer sentiment (Williams et al., 2024). This makes them less effective for analysing rapidly evolving perceptions or large-scale datasets in dynamic fields like emerging food technologies.

In recent years, there has been a growing adoption of more novel data collection and analysis approaches in the field, including the examination of comments on newspaper websites (Laestadius and Caldwell, 2015; Goodwin and Shoulders, 2013), blog posts (Laestadius, 2015), and discussions on social media platforms such as X (formerly Twitter), Facebook, and YouTube (Nautiyal and Lal, 2025; Molenaar et al., 2024; Singgalen, 2022; Feldmeyer and Johnson, 2022; Carr et al., 2015).

Previous studies on YouTube comments have demonstrated their utility in understanding public opinion and topic popularity (Meghana, 2024; Saikia et al., 2023). However, these analyses often exclude creator perspectives, which are critical in shaping narratives that influence audience sentiment. The lack of integration between these perspectives results in a fragmented understanding of how innovations are perceived and discussed. Bridging this gap by examining how narratives in video transcripts align, or diverge, from audience reactions in comments is important for comprehending the dynamics of societal acceptance (Yousefi et al., 2024; Banovic and Grunert, 2023).

To dive into consumer sentiment and public perceptions, natural language processing and text mining tools are essential. In recent studies, sentiment analysis and topic modelling are commonly applied in consumer perception analysis (Tao et al., 2020). Sentiment analysis is a powerful tool for extracting meaningful insights from large volumes of textual data. It enables organisations to gain a quick understanding overall attitude of a community toward a particular subject by evaluating their emotions and opinions, supporting more informed and strategic decision-making (Jim et al., 2024; Savci and Das, 2023). Topic modelling encompasses a range of techniques widely used to uncover the semantic structure within a dataset, focusing on identifying key concepts and themes (Vidal et al., 2022).

Sentiments are typically classified into three categories: positive, negative, and neutral (Antonakaki et al., 2021). Positive sentiments indicate confidence, optimism, and hopefulness regarding the subject, while negative sentiments reflect pessimism or a focus on its potential drawbacks or adverse consequences (Barbosa and Gomes, 2025).

Topic modelling methods, such as Latent Dirichlet Allocation (LDA), Biterm Topic Modelling (BTM) and BERTopic, have been widely used to uncover themes in consumer perceptions. LDA is a popular choice but struggles with short texts due to data sparsity, limiting its ability to reliably infer semantic relationships (Yan et al., 2013). While BTM addresses some issues with short texts, it lacks the ability to fully capture semantic dependencies (Zhen et al., 2022). Under this subject, BERTopic offers clear advantages by combining neural embeddings with clustering and c-TF-IDF, allowing for more coherent and context-aware topic representations (Grootendorst, 2022). Its integration of Sentence-BERT embeddings enables richer semantic insights and has been shown to outperform LDA in coherence scores and clustering quality (Ogunleye et al., 2023). This makes it a powerful tool for analysing complex narratives and supporting strategies to enhance the adoption of innovations like precision fermentation.

Overall, the combination of topic modelling and sentiment analysis has been utilised in many research studies (S.-H. Huang et al., 2022). By applying topic modelling to identify thematic clusters and sentiment analysis to capture public perceptions, researchers can generate actionable insights into how these technologies are framed and received. Such an approach not only advances academic understanding but also supports and provides insights and strategies for promoting sustainable food innovations. This study focuses specifically on perceptions of precision fermentation. By examining the narratives crafted by creators and the reactions of consumers, this research integrates these two perspectives to provide a comprehensive understanding of societal perceptions. The findings aim to offer valuable insights into fostering broader acceptance and adoption of precision fermentation technologies.

3. Dataset

The data for this study was collected from YouTube, focusing on video transcripts and comments from 1 January 2018 to 1 November 2024. Videos were selected based on their relevance to topics such as precision fermentation, lab-grown dairy, and related products. Transcripts were extracted using youtube-transcript-api. Both manual and auto-generated transcripts were included in the dataset, offering a comprehensive representation of the video content. To ensure consistency and clarity, non-English comments and videos were excluded during the data filtering process, retaining only English-language content. The final dataset comprises 345 videos with associated transcripts and 16,428 comments. The following Table 1 gives a summary of the characteristics of the dataset.

Unlike most previous studies that focus on single-layer data sources, such as tweets or survey responses, this research uses YouTube's dual-layer data: video transcripts and audience comments. This approach bridges the gap between public sentiment and content creator framing, offering a more comprehensive understanding of how narratives are constructed and received. The YouTube API further streamlines data collection, significantly reducing time and effort compared to traditional methods.

Since precision fermentation is a niche and highly technical subject, it remains relatively unknown to the general public and is not widely discussed in everyday contexts. As a result, a simple search for "precision fermentation" yielded a limited number of videos and comments, most of which were introductory or academic by nature, often targeting researchers or students. This presented challenges for analysing broader public sentiment. To address this, we expanded our search to include terms more relatable to everyday audiences, such as "lab-grown dairy" and specific precision fermentation-based products like Brave Robot ice cream (Nielsen et al., 2024). These products utilise precision fermentation technology and are more commonly recognised in public discussions. This broader approach allowed us to collect more data points and capture a more diverse range of relevant content. The selected videos were created by influencers, industry professionals, and academic experts, ensuring a variety of perspectives within the dataset (see Table 2).

Regarding the timeframe, many survey-based studies or studies utilising social media platforms focus on data collected over relatively short periods, such as a single year or less than a month (Muiruri and Rickertsen, 2024; Parrella et al., 2024; Feldmeyer and Johnson, 2022), or are based on reaching a specific number of available posts rather than a defined time frame(S. Ma et al., 2024). Given that precision fermentation is less widely recognised among the general public, this study opted for a longer timeframe to ensure a sufficient number of data points for analysing trends in topic popularity, changes in public sentiment, and evolving discussions over time. The selected period was designed to capture key milestones in the development of precision fermentation technologies and the public availability of related products. For instance, in 2018, Perfect Day partnered with ADM to commercialise animal-free dairy proteins, marking a significant step in transitioning from experimental stages to production (Watson, 2018). This timeframe enabled the collection of more comprehensive data and provided insights into potential shifts in public perceptions as the field evolved. By adopting this extended timeframe and broadening the scope of search terms, we aimed to offer a richer understanding of the evolution of public discourse and perceptions of precision fermentation.

4. Methodology

4.1. Analysis framework

To examine public perceptions of precision fermentation, we developed a streamlined analysis framework integrating natural language processing techniques for topic modelling and sentiment analysis (Fig. 1). This framework enabled the identification of key themes and emotional tones within a large volume of YouTube video transcripts and comments. The workflow involved three main components: data preprocessing, where the text was cleaned and standardised to remove noise and ensure consistency; sentiment analysis, which applied GPT-4o to classify viewer attitudes as positive, neutral, or negative; and topic modelling, using BERTopic to uncover latent thematic structures in the dataset. Fig. 1 provides a visual overview of the entire process, from data extraction to output interpretation. This modular framework supports rapid, scalable text analysis and is adaptable to various food technology domains.

Table 1
Summary of the precision fermentation dataset.

Dataset Attribute	Value
Total videos	345
Total comments	16,428
Average video view count	29,983
Average video like count	1,012
Average transcript length (words)	2776
Average transcript length (characters)	14,876
Average comment length (words)	28
Average comment length (characters)	150

Table 2
Distribution of YouTube topics in precision fermentation-related videos.

YouTube Topic	Count
Health	186
Knowledge	140
Business	72
Society	63
Food	50
Lifestyle	40
Others (Television Program, Entertainment, Film, Humor, Religion, Politics, Unknown)	145

**Note.* Topic categories in Table 2 are based on YouTube's built-in classification system, either selected by content creators or inferred by the platform. They reflect the general theme of each video prior to our analysis.

4.2. Data collection

As discussed in the Background and Related Work section, traditional methods such as surveys and interviews, while valuable, are often limited in scalability and responsiveness. To address these limitations, this study employs YouTube as a data source, providing access to a large volume of naturally occurring, real-time discourse on emerging food technologies.

Videos were sourced using keyword-based searches related to precision fermentation, including the technical term "precision fermentation," more widely recognised phrases such as "lab-grown dairy," and branded product names associated with the technology. This sourcing strategy was designed to ensure both technical relevance and broader public accessibility, enabling the inclusion of content targeted at diverse audiences. Both video transcripts and viewer comments were collected to capture two interconnected dimensions: how precision fermentation is framed by content creators, and how these narratives are interpreted, challenged, or reinforced by viewers.

Transcripts were retrieved using the YouTube Transcript API, while comments were collected via the CommentThreads endpoint of the YouTube Data API. This approach enables the integration of creator framing and spontaneous audience sentiment within a single, platform-based context.

4.3. Data preprocessing

The textual data from transcripts and comments underwent several preprocessing steps to ensure it was clean, consistent, and suitable for analysis. First, all text was converted to lowercase to eliminate inconsistencies caused by case sensitivity, such as treating "Precision" and "precision" as different words (Mikolov et al., 2013). Following this, contractions like "can't" were expanded to their full forms "cannot," ensuring that the complete semantic value of the text was retained. Special characters, emojis, and other non-alphanumeric symbols were removed to reduce noise in the data. These elements do not contribute to the core meaning of the text and could interfere with analysis (Chan and Li, 2024). Lemmatisation was applied to reduce words to their base forms, enabling the grouping of semantically similar terms and improving thematic and sentiment analyses. Stopword removal was

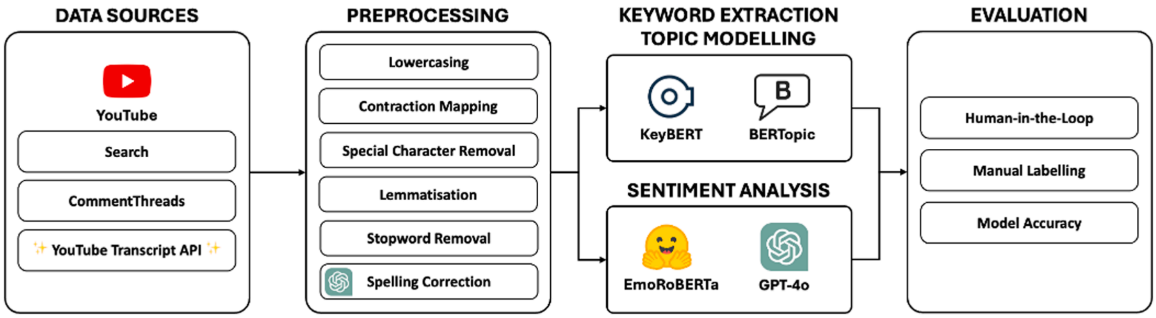

Fig. 1. Analysis framework.

another critical step in the preparation process (Vidal et al., 2022; Bao et al., 2014). Commonly used words such as "and," "is," and "the" were excluded as they do not add significant meaning to the text. This allowed the analysis to focus on the more informative words and phrases. Finally, spelling corrections were made using the OpenAI API, which offered high accuracy and adaptability to domain-specific language, ensuring cleaner and more reliable text for analysis (Dashti et al., 2024; Martynov et al., 2023). By performing these preprocessing steps, we optimised the dataset for downstream analysis, ensuring that the text retained its semantic richness while minimising noise and irrelevant elements.

4.4. Topic modelling

To extract and understand dominant themes within the textual data, we employed BERTopic, a topic modelling method that leverages transformer-based embeddings, UMAP for dimensionality reduction, and HDBSCAN for clustering (Barbosa and Gomes, 2025; George and Sumathy, 2023). The BERTopic workflow can be summarised in four main stages (see Fig. 2). First, textual data is converted into numerical representations that capture semantic similarity. Second, UMAP reduces these high-dimensional embeddings to a lower-dimensional space to enable pattern recognition. Third, HDBSCAN clusters similar texts while filtering out noise and outliers. Finally, keywords are extracted for each cluster to facilitate interpretation and summarise core themes. This layered approach enables the identification of recurring concerns and dominant frames across large-scale datasets.

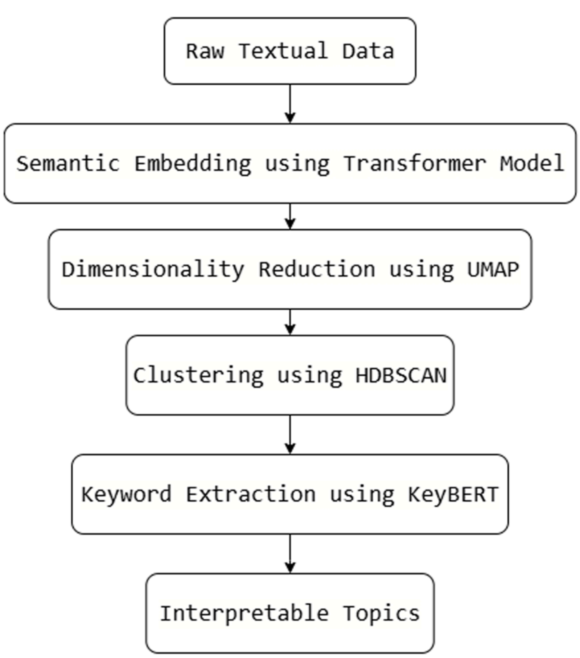

Fig. 2. Workflow of topic modelling using BERTopic.

In this study, the transcripts were pre-processed to remove noise and standardise the text before being encoded using the all-MiniLM-L6-v2 SentenceTransformer model (Salahudeen et al., 2024). The embeddings were then reduced to a lower-dimensional space using UMAP, optimised for clustering with moderate granularity (McInnes et al., 2020). HDBSCAN was employed to identify clusters, which were then interpreted as topics (Barbosa and Gomes, 2025; Campello et al., 2013). HDBSCAN identifies clusters of different densities through a hierarchical clustering algorithm that prevents misclassification of unrelated documents into clusters by clearly identifying outliers and, hence, improving topic representation (Gupta et al., 2024). This approach was chosen for its ability to identify coherent and interpretable topics within complex datasets (George and Sumathy, 2023) and has been adopted in other studies due to its superior performance (Barbosa and Gomes, 2024, Gregoriades et al., 2021).

Overall, this combination allowed us to identify distinct themes while accounting for subtle variations within the data. Keywords associated with each topic were extracted using KeyBERT, ensuring the interpretability of the clusters (Pęzik et al., 2022). This process not only provided insights into the broader discourse but also identified specific topics linked to consumer concerns and perceived benefits, such as cost, nutritional value, and environmental sustainability.

4.5. Sentiment analysis

Sentiment analysis was conducted to evaluate public perceptions of precision fermentation. The analysis classified sentiments into three categories: positive, negative, or neutral. Two models, EmoRoBERTa and OpenAI GPT-4o (Krugmann and Hartmann, 2024; Belal et al., 2023), were assessed through a manual review of 300 randomly selected data points to validate their accuracy (Hartmann et al., 2023; van Atteveldt et al., 2021; Gohil et al., 2018). This approach can evaluate how well the model's predictions aligned with human-validated sentiment labels.

The evaluation revealed that GPT-4o achieved an accuracy of 76 %, surpassing EmoRoBERTa at 66 %, demonstrating its reliability for conducting quick and accurate sentiment classification within the domain. Additionally, GPT-4o demonstrated a significantly faster runtime, requiring less than one-tenth of the time compared to EmoRoBERTa. The use of prompt engineering further enhanced GPT-4o's ability to adapt to domain-specific language, ensuring more reliable and relevant sentiment classification. Based on these advantages, GPT-4o was selected for this study.

A visual summary of the GPT-4o sentiment classification process is shown in Fig. 3, illustrating the steps from data input to sentiment output. Leveraging OpenAI's API, GPT-4o provided flexible and accurate sentiment classification, particularly in efficiently handling domain-specific language. For transcripts, the process focused on segments related to specific topics such as "lab-grown dairy," "precision fermentation," and "alternative proteins." This targeted approach ensured the

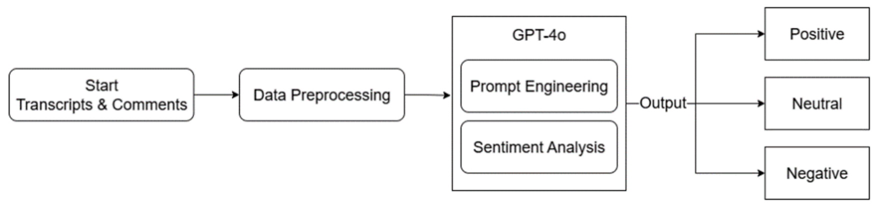

Fig. 3. GPT-4o-based sentiment analysis framework.

exclusion of irrelevant content during sentiment analysis, thereby enhancing the relevance and precision of the results.

5. Results

Overall, the number of precision fermentation-related videos on YouTube has demonstrated a rapid and steady increase, reflecting growing attention to this topic (see Fig. 4). In 2018, there were no relevant videos available on the platform. Starting in 2019, from <5 videos, the numbers began to climb rapidly with the progresses in this field, to >100 videos published in 2023, and the number of videos in the first ten months of 2024 had already surpassed the total number of precision fermentation-related videos for the entire 2023. This trend highlights an increasing awareness and interest in the potential of this emerging technology and its related products among content creators.

The view count and like count exhibited similar trends, with peaks observed in Q1 and Q3 of 2022, significantly surpassing any other periods (see Fig. 5 and Fig. 6).

The trend in comments over time also reveals interesting dynamics in audience engagement with precision fermentation-related videos. Initially, despite the extremely limited number of videos, comments reached over 1000 in 2019. However, while the number of videos rapidly increased and multiplied several times over the following two years, the number of comments decreased slightly until 2022, when audience engagement began to rise significantly again and hit its peak in 2023 (see Fig. 7). August 2023, in particular, stood out with over 3000 comments in a single month. Following this peak, audience engagement dropped sharply but started to recover noticeably by the third quarter of 2024.

Overall, the trends in both video and comment activity reflect that, despite fluctuations in the topic's popularity, it is steadily gaining more and more attention.

The creator-driven sentiment analysis revealed that among the 345 videos retrieved from YouTube, the sentiment distribution in transcripts exhibited a predominantly positive tone, with 67.83 % (234 videos) of the videos classified as positive, 28.99 % (100 videos) as neutral, and only 3.19 % (11 videos) as negative.

In this study, based on YouTube's video categorisation, the retrieved videos were predominantly from the Health and Knowledge categories, followed by Business, Society, and Food. In terms of sentiment distribution across these categories, the patterns were relatively consistent, with positive sentiment being the most prevalent, followed by neutral and then negative sentiment.

Over time, videos with positive sentiment have consistently been the majority, except in 2019, when videos with negative sentiment accounted for over half of the related videos that year (see Fig. 8). However, this may be attributed to the limited number of data points in 2019, making it challenging to confirm the reliability of this distribution. Following 2019, the number of videos with negative sentiment dropped sharply and has remained below 5 % of the total number of precision fermentation-related videos published annually since 2021. In contrast, videos with positive sentiment have accounted for over 60 % of related videos each year since 2020, reaching 75 % in 2023, the highest proportion of positive sentiment to date. This suggests that creators, including influencers, industry professionals, and academics, tend to frame precision fermentation technologies in a more optimistic and forward-looking manner.

This trend aligns with the advancements in precision fermentation, such as the commercialisation of animal-free dairy proteins in 2018, increased public awareness campaigns by companies, and the growing availability of precision-fermented foods in certain regions of Europe and America in recent years (Andersson and Borgernäs, 2024; Ho, 2024; Yap et al., 2024; Terefe, 2022).

Regarding the comments, after preprocessing, a total of 16,428 comments were analysed. Among these, 46.64 % were neutral, 34.7 % negative, and 18.66 % positive. Interestingly, negative sentiments outweighed positive ones, despite the overall optimism observed in video transcripts.

Over time, as the topic gained increasing attention, the proportion of negative sentiment comments also rose (see Fig. 9). Between 2019 and

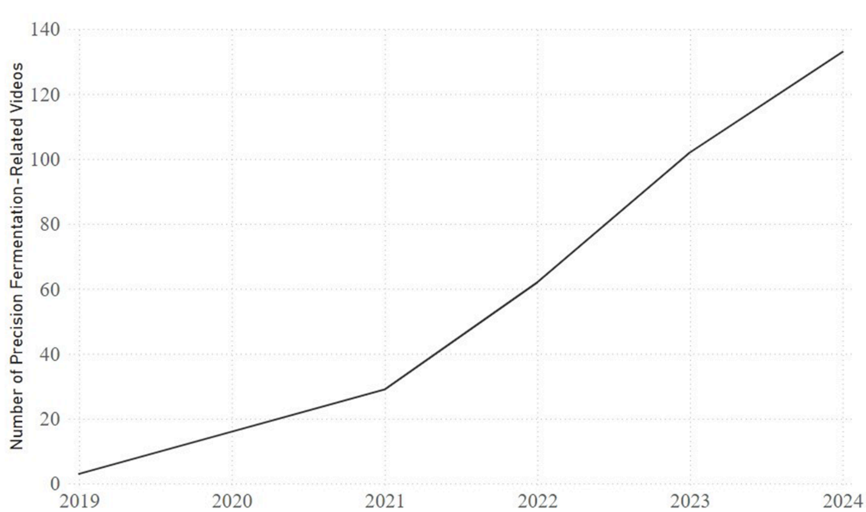

Fig. 4. Trend in the number of precision fermentation-related videos.

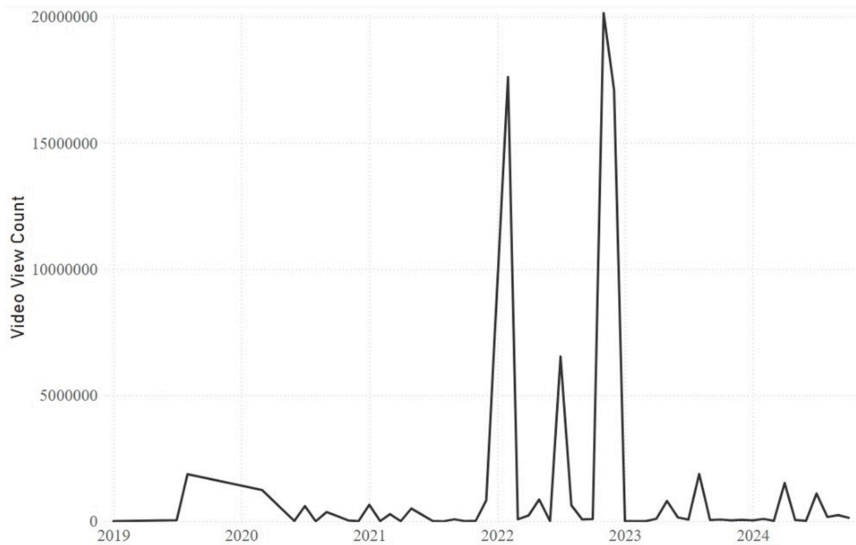

Fig. 5. Trend in the video view count over time.

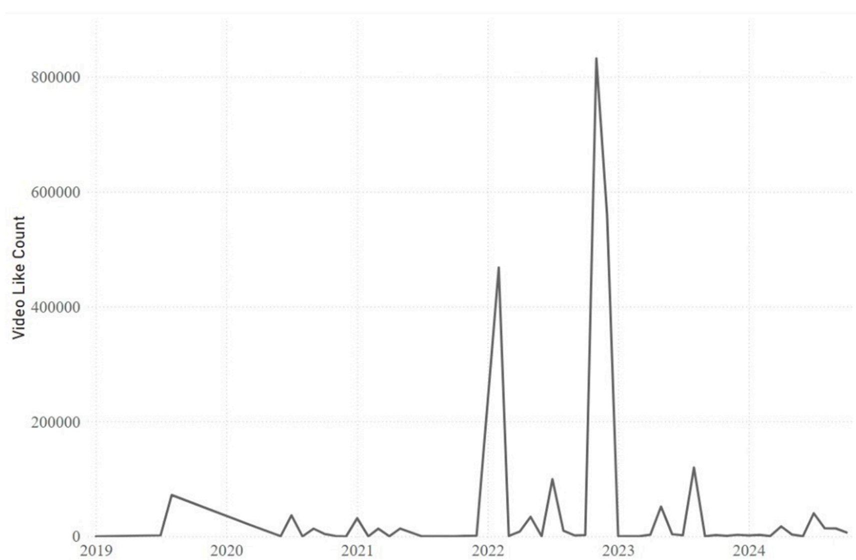

Fig. 6. Trend in the video like count over time.

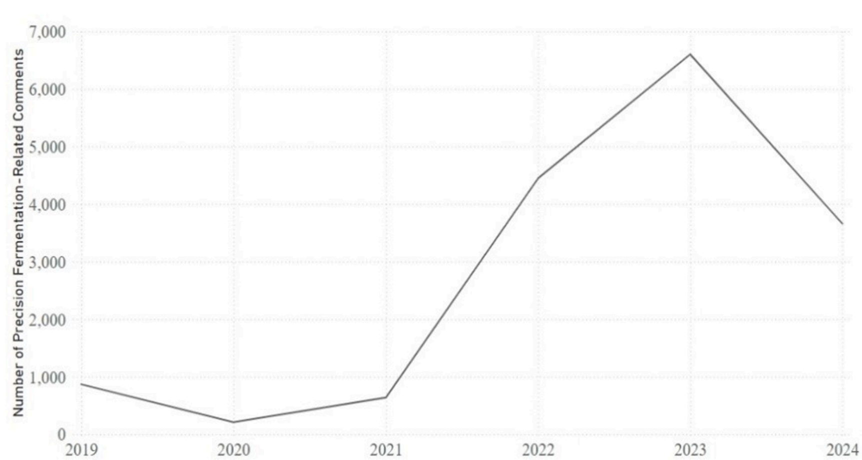

Fig. 7. Trend in the number of precision fermentation-related comments.

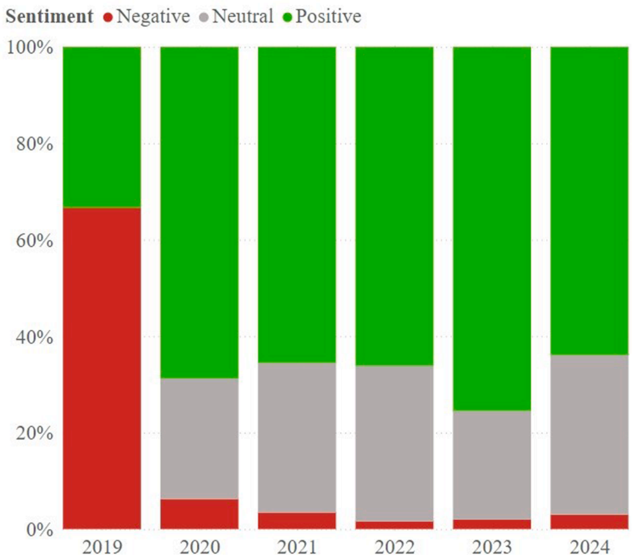

Fig. 8. Sentiment distribution of precision fermentation-related videos over time.

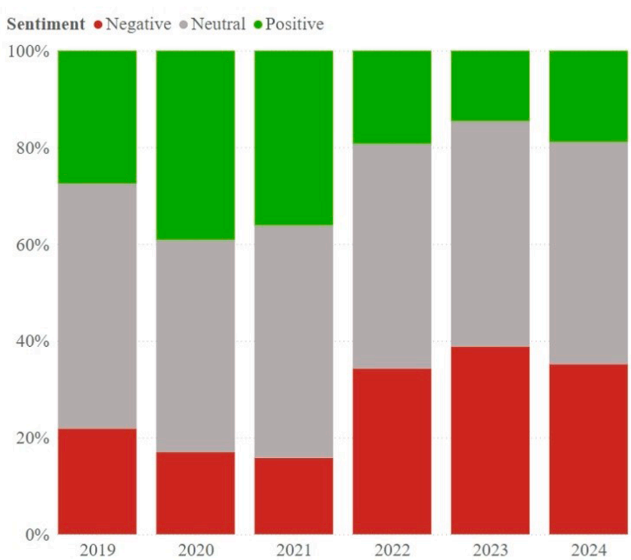

Fig. 9. Sentiment distribution of comments over time.

2021, negative sentiment remained relatively low, hovering around or below 20 %. However, starting in 2022, when the topic's popularity surged, the proportion of negative comments rose sharply, exceeding 30 % in that year. It peaked at 38.78 % in 2023 before slightly declining but remained above 35 % in the first 10 months in 2024. In contrast, neutral comments showed a relatively stable trend, consistently fluctuating around 50 %. Positive comments, however, have seen a notable decline, from a peak of 39.15 % in 2022 to below 20 % in the past three years.

Overall, while videos on precision fermentation generally exhibit a predominantly positive sentiment, reflecting creators' optimism and advocacy for the technology, audience reactions in comments remain more polarised, with scepticism and concerns becoming increasingly visible.

Using BERTopic, we clustered the videos into 34 distinct topics (see Fig. 10). The identified topics included areas related to consumer perceptions, environmental benefits, and technical aspects of precision fermentation. For example, some clusters revealed concerns about the scalability of fermentation technologies, while others highlighted the potential for animal-free dairy products to address ethical concerns. These 34 clusters were then manually grouped into three broader categories: Dairy and Milk Products, Other Alternative Proteins and Sustainable Foods, and Precision Fermentation and Processes (see Fig. 11). Among these, videos in the Other Alternative Proteins and Sustainable Foods category had the highest proportion of negative sentiment in comments, accounting for 51.11 %. This is significantly higher than the other two clusters, indicating more audience scepticism or concerns in this area. In contrast, the Dairy and Milk Products category had the lowest proportion of negative sentiment in its comments, with only 23.07 %. Neutral sentiment dominated in the comments of this cluster, making up around 50 % of the total.

6. Discussion & conclusion

This study provides a comprehensive exploration of public perceptions of precision fermentation technologies by analysing YouTube videos and associated comments. Using advanced natural language processing methods, it uncovers a dual narrative in the discourse surrounding precision fermentation.

Under this specific topic, for the sentiment of content creators, based on our observations, most creators overwhelmingly express positive sentiment. Among the three sentiments we studied, we found that the consistent optimism among most creators likely reflects their roles as advocates or educators, aiming to present precision fermentation as an innovative solution to global food challenges. Some creators may also be driven by enthusiasm for new products that align with ethical and environmental values or potentially funded by companies producing related products to highlight their benefits and foster positive public feedback. Neutral sentiments often stem from a focus on informational content, such as explaining fermentation processes or the science behind the technology. The low proportion of negative sentiment in creator-driven content suggests that creators might deliberately avoid controversy, possibly to maintain credibility, align with industry interests, or respond to algorithmic incentives that favour positive content.

While creators predominantly emphasised the positive aspects of precision fermentation, audience comments reflected greater scepticism, raising concerns about affordability, scalability, and health implications. This divergence aligns with previous research on public responses to novel food technologies. For example, studies have shown a persistent gap between optimistic messaging from promoters and the cautious attitudes of consumers, especially when technologies are perceived as unfamiliar or unnatural (Albertsen et al., 2018). Psychological factors such as food neophobia and lack of trust are also known to play significant roles in shaping resistance to food innovations (Siddiqui et al., 2022), which helps explain the heightened negativity observed in many audience comments.

The consistent optimism found in creator sentiment supports earlier findings that creators often act as advocates or educators, driven by ideological, ethical, or commercial motivations (X. Ma, 2023). Similar promotional dynamics have been observed in adjacent areas like plant-based proteins and lab-grown meat, where public communicators tend to highlight benefits while downplaying risks (Choi et al., 2024; Tsvakirai et al., 2024). Our findings extend this literature by showing that such optimism does not necessarily carry over to consumer sentiment, particularly in open, interactive platforms like YouTube where audiences express direct feedback.

The three video clusters, Dairy and Milk Products, Other Alternative Proteins and Sustainable Foods, and Precision Fermentation and Processes, further highlighted this divide. Videos in the Dairy and Milk Products category had the lowest proportion of negative sentiment in comments (23.07 %), likely due to greater consumer familiarity and cultural acceptance of these products. Most publicly available precision fermentation products on the market currently are dairy-based, such as milk, cheese, and ice cream, which are frequently featured in product review videos on YouTube. In contrast, videos under Other Alternative

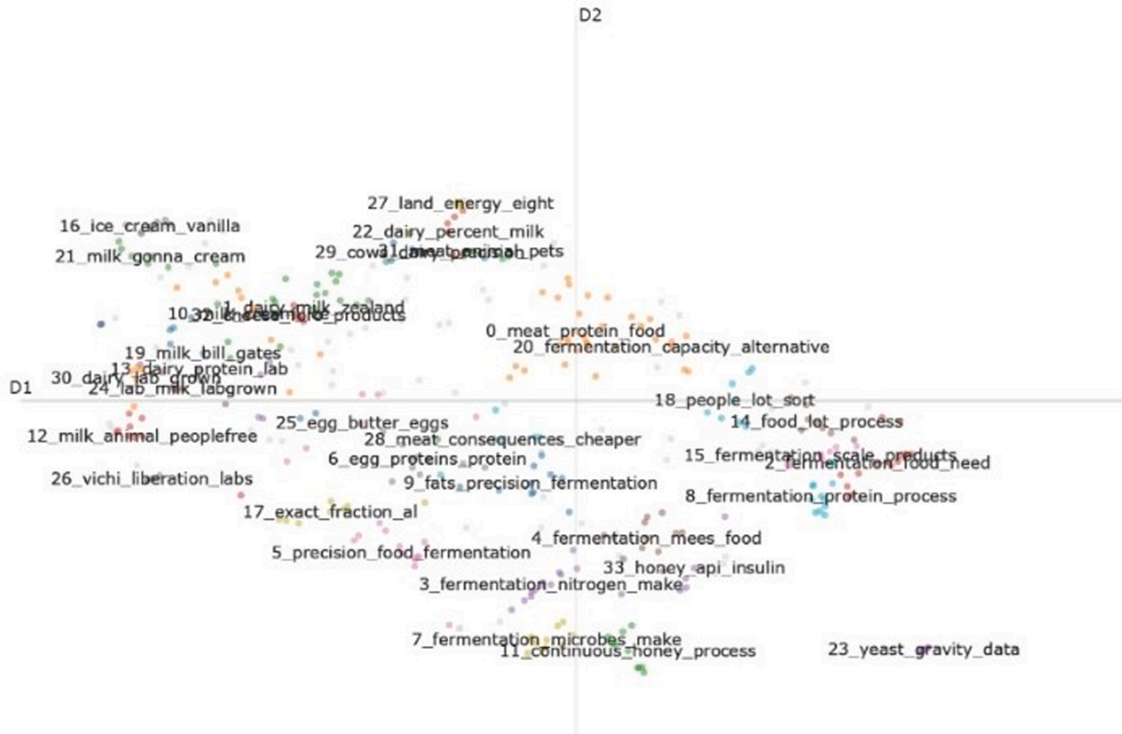

Fig. 10. BERTopic clusters of precision fermentation-related videos.

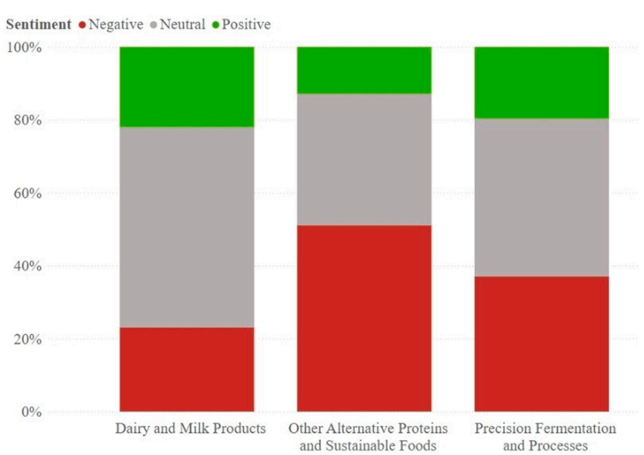

Fig. 11. Sentiment distribution across three key categories of precision fermentation-related videos.

Proteins and Sustainable Foods saw 51.11 % of their comments classified as negative, reflecting heightened scepticism toward less familiar technologies or concepts perceived as distant from everyday experiences, consistent with research showing that perceived unnaturalness and psychological distance reduce consumer acceptance (Siegrist, 2020).

Overall, the increasing number of precision fermentation-related videos and comments over time highlights growing interest and awareness among both creators and audiences. However, the rising proportion of negative sentiment in audience comments, particularly in recent years, suggests that the increased visibility of precision fermentation products has potentially led to heightened public scrutiny and amplified concerns. This underscores the need for more transparent, evidence-based communication strategies that directly address consumer concerns. While public engagement with precision fermentation remains polarised, the consistent optimism of creators presents an opportunity to thoughtfully counterbalance consumer scepticism (Choi et al., 2024; Tsvakirai et al., 2024). By leveraging advanced analytical tools and adopting inclusive, transparent communication strategies, stakeholders can align public perceptions with the broader goals of sustainability and innovation, paving the way for the successful adoption of precision fermentation and other transformative food technologies.

The approach outlined in this study offers a scalable framework for continuous sentiment tracking and topic discovery, which is crucial for studying consumer perceptions of food products. By leveraging advanced natural language processing tools and models like BERTopic and GPT-4o, this framework enables real-time monitoring of public discourse, identifying emerging trends and consumer sentiments. The proactive insights gained through this framework can assist in navigating the complexities of market adoption, supporting the sustainable expansion of innovative food technologies, and helping companies to establish market entry strategies, refine communication plans, and foster product growth by addressing consumer concerns promptly and effectively.

Beyond its application to precision fermentation, the methodological framework employed in this study demonstrates significant potential for analysing perceptions of other innovative technologies, such as lab-grown meat, gene-edited crops, and sustainable packaging solutions. As this methodology evolves, it offers a scalable pathway for continuous monitoring and analysis of public discourse surrounding innovative technologies. By combining sentiment tracking, topic discovery, emotional analysis, and socio-economic and cultural considerations, it provides actionable insights for stakeholders. This comprehensive approach enables effective consumer engagement, proactive issue resolution, and broader acceptance. Such capability is critical for industries navigating public opinion and ensuring smoother transitions from innovation to market adoption, especially in areas where ethical considerations and trust are paramount.

7. Limitations and future works

The methodology employed in this study proved critical for understanding the interplay between creator narratives and audience perceptions. BERTopic enabled the clustering of videos into coherent topics, offering a structured view of key discourse areas, while OpenAI GPT-4o provided precise sentiment classification. However, this study also has notable limitations that should be acknowledged.

First, this study focused on broad sentiment categories (positive, negative, neutral) without exploring finer emotional states such as disgust, surprise, or curiosity. Analysing specific emotions could provide deeper insights into psychological engagement and resistance, potentially sustaining public interest in early-stage innovations (Nandwani and Verma, 2021). However, this lack of granularity limits the depth of insights derived from consumer perception, particularly in detecting nuances like sarcasm, irony, or culturally specific expressions, which are common in food-related discussions.

While we ideally would have pursued a more detailed emotional analysis, the reality of data availability constrains such efforts. This limitation arises from the lack of diverse, high-quality data that distinctly expresses a range of emotions. At present, most audiences lack sufficient knowledge or interest to form strong opinions or exhibit varied emotions. Public perceptions of precision fermentation largely remain neutral or ambiguous, with insufficient granularity to support robust emotional analysis.

When new technologies enter the market, particularly in their early years, the volume of available data and the diversity of emotions expressed by the public are inherently limited, which is a common challenge in such contexts. However, as the quantity and richness of data grow, allowing for more varied and nuanced emotional expressions, there will be a point where we could build upon this foundation to move beyond basic sentiment analysis to more nuanced emotional assessments. This progression will enable more sophisticated emotional assessments, facilitating a transition from early-stage analysis to a deeper, more nuanced understanding of consumer perceptions.

Another limitation relates to audience representation. Despite efforts to include a range of search terms, precision fermentation and its related products remain niche topics with limited visibility in mainstream discussions. Consequently, the dataset likely reflects an overrepresentation of academically inclined, scientifically informed, or environmentally conscious audiences familiar with the technology. This imbalance may result in findings that do not fully capture the perspectives of the general public, who are less aware of or engaged with these topics.

The dataset also has inherent limitations. By restricting the analysis to English-language videos and comments, the study introduces a geographic and cultural bias. This focus inherently skews the dataset toward English-speaking regions, reducing its applicability to non-English-speaking areas such as Europe and Asia, where meaningful discussions on precision fermentation might also be taking place. This constraint limits the generalisability of the findings to a global context. Additionally, the inclusion of auto-generated transcripts introduces potential inaccuracies, especially in domain-specific terminology. These inaccuracies, although minor, could lead to inconsistencies in sentiment analyses and affect the reliability of the research.

Future research could address these limitations by expanding the analysis to multilingual datasets, incorporating multimodal data such as visual and auditory cues, and leveraging domain-specific dictionaries to enhance the contextual understanding of technical terms. For instance, combining industry-specific glossaries with large language models could refine sentiment classification and improve accuracy in specialised and rapidly evolving fields. Additionally, utilising cross-platform data from various social media channels could provide a more representative picture of public discourse, considering the preferences of different demographics across platforms.

Despite these limitations, the approach outlined in this study offers a quick and effective way to gain early-stage insights into public sentiment. As this methodology evolves, it provides a scalable framework for analysing consumer perceptions, which can be refined and expanded as more comprehensive data becomes available. This serves as a critical foundation for understanding public engagement with precision fermentation and other emerging food technologies, paving the way for deeper analyses and improved communication strategies in the future.

Declaration of generative AI in scientific writing

During the preparation of this work the authors used ChatGPT in order to perform grammatical corrections. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Ethical statement

This work does not involve human; data were sourced from YouTube, a publicly accessible digital platform for video sharing and commenting, without any personal identifiable information collected.

CRediT authorship contribution statement

Johnny Chan: Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Yilong Wang:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Brice Valentin Kok-Shun:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Meng Wai Woo:** Resources, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

References

Albertsen, L., Wiedmann, K.-P., Karampournioti, E., Langner, S., 2018. An abstract: consumer's acceptance of food innovations: effects on product perception and consumer behavior. In: Krey, N., Rossi, P. (Eds.), Boundary Blurred: A Seamless Customer Experience in Virtual and Real Spaces. Springer International Publishing. https://doi.org/10.1007/978-3-319-99181-8_165 (pp. 505–505).

Alhujaili, R.F., & Yafooz, W.M.S. (2021). Sentiment analysis for youtube videos with user comments: review. 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), 814–820. https://doi.org/10.1109/ICAIS50930.2021.9396049.

Andersson, A., Borgernäs, S., 2024. Scaling up precision fermentation of dairy proteins: a chicken and egg problem. https://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-353399.

Antonakaki, D., Fragopoulou, P., Ioannidis, S., 2021. A survey of Twitter research: data model, graph structure, sentiment analysis and attacks. Exp. Syst. Appl. 164, 114006. https://doi.org/10.1016/j.eswa.2020.114006.

Appiani, M., Cattaneo, C., Laureati, M., 2025. Plant-based fish analogues vs. fish: assessment of consumer perception, acceptance, and attitudes. Food Qual. Prefer. 123, 105329. https://doi.org/10.1016/j.foodqual.2024.105329.

Banovic, M., Asioli, D., Sogari, G., 2025. Cross-cultural consumer valuation of precision fermentation milk: effects of information, individual traits, and labelling preferences. Food Qual. Prefer. 131, 105570. https://doi.org/10.1016/j.foodqual.2025.105570.

Banovic, M., Grunert, K.G., 2023. Consumer acceptance of precision fermentation technology: a cross-cultural study. Innovat. Food Sci. Emerg. Technol. 88, 103435. https://doi.org/10.1016/j.ifset.2023.103435.

Bao, Y., Quan, C., Wang, L., Ren, F., Wang, L., 2014. The role of pre-processing in Twitter sentiment analysis. In: Huang, D.-S., Jo, K.-H. (Eds.), Intelligent Computing Methodologies. Springer International Publishing, pp. 615–624. https://doi.org/10.1007/978-3-319-09339-0_62.

Barbosa, M.W., Gomes, A., 2025. Themes and sentiments in conversations about food waste on Twitter: proposal of a framework using neural topic modeling. Food Qual. Prefer. 122, 105311. https://doi.org/10.1016/j.foodqual.2024.105311.

Belal, M., She, J., & Wong, S. (2023). *Leveraging ChatGPT As text annotation tool for sentiment analysis* (No. arXiv:2306.17177). arXiv. https://doi.org/10.48550/arXiv.2306.17177.

Bhuiyan, H., Ara, J., Bardhan, R., & Islam, Md.R. (2017). Retrieving YouTube video by sentiment analysis on user comment. *2017 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, 474–478. https://doi.org/10.1109/ICSIPA.2017.8120658.

Bryant, C.J., Barnett, J.C., 2019. What's in a name? Consumer perceptions of in vitro meat under different names. Appetite 137, 104–113. https://doi.org/10.1016/j.appet.2019.02.021.

Cai, G., Shen, C., Wu, X., Ding, M., Zhao, T., Li, Y., Wang, B., Liu, D., 2024. Insights on purchase intention of mutton shashlik—a survey of Chinese consumers based on fsQCA. Future Foods. 10, 100446. https://doi.org/10.1016/j.fufo.2024.100446.

Campello, R.J.G.B., Moulavi, D., Sander, J., 2013. Density-based clustering based on hierarchical Density estimates. In: Pei, J., Tseng, V.S., Cao, L., Motoda, H., Xu, G. (Eds.), Advances in Knowledge Discovery and Data Mining. Springer, pp. 160–172. https://doi.org/10.1007/978-3-642-37456-2_14.

Carr, J., Decreton, L., Qin, W., Rojas, B., Rossochacki, T., Yang, Y.Wen, 2015. Social media in product development. Food Qual. Prefer. 40, 354–364. https://doi.org/10.1016/j.foodqual.2014.04.001.

Chan, J., Li, Y., 2024. Unveiling disguised toxicity: a novel pre-processing module for enhanced content moderation. MethodsX. 12, 102668. https://doi.org/10.1016/j.mex.2024.102668.

Chen, A., Lim, A.J., Lin, J.W.X., Oh, G., Teo, P.S., Bowie, D., Deb-Choudhury, S., Samuelsson, L.M., Chan, J.C.Y., Ng, S.B., Foster, M., Giezenaar, C., Hort, J., 2024. Perception and acceptance of high seaweed content novel foods (*Ulva* spp. And *Undaria pinnatifida*) across New Zealand and Singaporean consumers. Future Foods. 10, 100511. https://doi.org/10.1016/j.fufo.2024.100511.

Choi, F., Lambert, C., Koshy, V., Pratipati, S., Do, T., & Chandrasekharan, E. (2024). *Creator Hearts: investigating the impact positive signals from YouTube creators in shaping comment section behavior* (No. arXiv:2404.03612). arXiv. https://doi.org/10.48550/arXiv.2404.03612.

Dashti, S.M.S., Khatibi Bardsiri, A., Jafari Shahbazzadeh, M., 2024. PERCORE: a deep learning-based framework for Persian spelling correction with phonetic analysis. Int. J. Computat. Intell. Syst. 17 (1), 114. https://doi.org/10.1007/s44196-024-00459-y.

Feldmeyer, A., Johnson, A., 2022. Using Twitter to model consumer perception and product development opportunities: a use case with Turmeric. Food Qual. Prefer. 98, 104499. https://doi.org/10.1016/j.foodqual.2021.104499.

Fytsilis, V.D., Urlings, M.J.E., van Schooten, F.-J., de Boer, A., Vrolijk, M.F., 2024. Toxicological risks of dairy proteins produced through cellular agriculture: current state of knowledge, challenges and future perspectives. Future Foods. 10, 100412. https://doi.org/10.1016/j.fufo.2024.100412.

George, L., Sumathy, P., 2023. An integrated clustering and BERT framework for improved topic modeling. Int. J. Informat. Technol. 15 (4), 2187–2195. https://doi.org/10.1007/s41870-023-01268-w.

Ghosh, A., Tripathi, S.D., 2025. Understanding viewer fascination with reaction videos: a discourse analysis of YouTube comments. Media Watch. 16 (2), 230–249. https://doi.org/10.1177/09760911241313236.

Gohil, S., Vuik, S., Darzi, A., 2018. Sentiment analysis of health care tweets: review of the methods used. JMIR Public Health Surveil. 4 (2), e5789. https://doi.org/10.2196/publichealth.5789.

Goodwin, J.N., Shoulders, C.W., 2013. The future of meat: a qualitative analysis of cultured meat media coverage. Meat Sci. 95 (3), 445–450. https://doi.org/10.1016/j.meatsci.2013.05.027.

Grootendorst, M. (2022). *BERTopic: neural topic modeling with a class-based TF-IDF procedure* (No. arXiv:2203.05794). arXiv. https://doi.org/10.48550/arXiv.2203.05794.

Hartmann, J., Heitmann, M., Siebert, C., Schamp, C., 2023. More than a feeling: accuracy and application of sentiment analysis. Int. J. Res. Market. 40 (1), 75–87. https://doi.org/10.1016/j.ijresmar.2022.05.005.

Hilgendorf, K., Wang, Y., Miller, M.J., Jin, Y.-S., 2024. Precision fermentation for improving the quality, flavor, safety, and sustainability of foods. Curr. Opin. Biotechnol. 86, 103084. https://doi.org/10.1016/j.copbio.2024.103084.

Ho, S., 2024. Animal free whey protein maker Perfect Day says goodbye to founders, raises up to $90M. Green Queen. https://www.greenqueen.com.hk/perfect-day-new-leadership-90-million-funding/.

Huang, S.-H., Tsao, S.-F., Chen, H., Bin Noon, G., Li, L., Yang, Y., Butt, Z.A., 2022. Topic modelling and sentiment analysis of tweets related to freedom convoy 2022 in Canada. Int. J. Public Heal. 67, 1605241. https://doi.org/10.3389/ijph.2022.1605241.

Jim, J.R., Talukder, M.A.R., Malakar, P., Kabir, M.M., Nur, K., Mridha, M.F., 2024. Recent advancements and challenges of NLP-based sentiment analysis: a state-of-the-art review. Nat. Lang. Process. J. 6, 100059. https://doi.org/10.1016/j.nlp.2024.100059.

Kossmann, H., Schulze, H., Mergenthaler, M., Breunig, P., 2023. Acceptance of animal-free cheese products: evidence from an information experiment in Germany. Food Qual. Prefer. 111, 104984. https://doi.org/10.1016/j.foodqual.2023.104984.

Krugmann, J.O., Hartmann, J., 2024. Sentiment analysis in the age of generative AI. Customer Needs Solut. 11 (1), 3. https://doi.org/10.1007/s40547-024-00143-4.

Kühl, S., Schäfer, A., Kircher, C., Mehlhose, C., 2024. Beyond the cow: consumer perceptions and information impact on acceptance of precision fermentation-produced cheese in Germany. Future Foods. 10, 100411. https://doi.org/10.1016/j.fufo.2024.100411.

Laestadius, L.I., 2015. Public Perceptions of the ethics of In-vitro meat: determining an appropriate course of action. J. Agric. Environment. Ethic. 28 (5), 991–1009. https://doi.org/10.1007/s10806-015-9573-8.

Laestadius, L.I., Caldwell, M.A., 2015. Is the future of meat palatable? Perceptions of in vitro meat as evidenced by online news comments. Public Health Nutr. 18 (13), 2457–2467. https://doi.org/10.1017/S1368980015000622.

Ma, S., Zheng, X.J., Lu, P., Xu, Z., 2024. Promoting Upcycled Food: an analysis of social media communication strategies of Upcycled Food Association. Future Foods. 10, 100483. https://doi.org/10.1016/j.fufo.2024.100483.

Ma, X., 2023. Incentives for digital content contribution. Manage. Profession. 15–40.

Martynov, N., Baushenko, M., Kozlova, A., Kolomeytseva, K., Abramov, A., & Fenogenova, A. (2023). *A methodology for generative spelling correction via natural spelling errors emulation across multiple domains and languages* (No. arXiv:2308.09435). arXiv. https://doi.org/10.48550/arXiv.2308.09435.

McCluskey, J.J., Kalaitzandonakes, N., Swinnen, J., 2016. Media coverage, public perceptions, and consumer behavior: insights from new food technologies. Annu. Rev. Resour. Econ. 8, 467–486. https://doi.org/10.1146/annurev-resource-100913-012630.

McInnes, L., Healy, J., & Melville, J. (2020). *UMAP: uniform manifold approximation and projection for dimension reduction* (No. arXiv:1802.03426). arXiv. https://doi.org/10.48550/arXiv.1802.03426.

Meghana, K. (2024). Artificial intelligence and sentiment analysis in YouTube comments: a comprehensive overview. *2024 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)*, 1565–1572. https://doi.org/10.1109/IDCIoT59759.2024.10467782.

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). *Efficient estimation of word representations in vector space* (No. arXiv:1301.3781). arXiv. https://doi.org/10.48550/arXiv.1301.3781.

Molenaar, A., Jenkins, E.L., Brennan, L., Lukose, D., McCaffrey, T.A., 2024. The use of sentiment and emotion analysis and data science to assess the language of nutrition-, food- and cooking-related content on social media: a systematic scoping review. Nutr. Res. Rev. 37 (1), 43–78. https://doi.org/10.1017/S0954422423000069.

Muiruri, S.W., Rickertsen, K., 2024. Norwegian consumers' willingness to try cultured meat. Future Foods. 10, 100409. https://doi.org/10.1016/j.fufo.2024.100409.

Nandwani, P., Verma, R., 2021. A review on sentiment analysis and emotion detection from text. Soc. Netw. Anal. Min. 11 (1), 81. https://doi.org/10.1007/s13278-021-00776-6.

Nautiyal, S., Lal, C., 2025. Eager or passive? Decoding potential consumer profiles based on knowledge and perceptions regarding organic food products. Food Qual. Prefer. 123, 105345. https://doi.org/10.1016/j.foodqual.2024.105345.

Nielsen, M.B., Meyer, A.S., Arnau, J., 2024. The next food revolution is here: recombinant microbial production of milk and egg proteins by precision fermentation. Annu. Rev. Food Sci. Technol. 15, 173–187. https://doi.org/10.1146/annurev-food-072023-034256.

Ogunleye, B., Maswera, T., Hirsch, L., Gaudoin, J., Brunsdon, T., 2023. Comparison of topic modelling approaches in the banking context. Appl. Sci. 13 (2). https://doi.org/10.3390/app13020797. Article 2.

Parrella, J.A., Leggette, H.R., Lu, P., Wingenbach, G., Baker, M., Murano, E., 2024. What's the beef with gene editing? An investigation of factors influencing U.S. consumers' acceptance of beef from gene-edited cattle. Future Food. 10, 100454. https://doi.org/10.1016/j.fufo.2024.100454.

Pęzik, P., Mikołajczyk, A., Wawrzyński, A., Nitoń, B., Ogrodniczuk, M., 2022. Keyword extraction from short texts with a text-to-text transfer transformer. In: Szczerbicki, E., Wojtkiewicz, K., Nguyen, S.V., Pietranik, M., Krótkiewicz, M. (Eds.), Recent Challenges in Intelligent Information and Database Systems. Springer Nature, pp. 530–542. https://doi.org/10.1007/978-981-19-8234-7_41.

Rachel J., J. L., A, B., & M, K. (2024). Topic modeling based clustering of disaster tweets using BERTopic. *2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon)*, 1–6. https://doi.org/10.1109/MITADTSoCiCon60330.2024.10575555.

Saikia, S., Kumar, V., Verma, M.K., 2023. Analyzing user sentiments toward selected content management software: a sentiment analysis of viewer's comments on YouTube. Inform. Discov. Deliv. 52 (4), 378–387. https://doi.org/10.1108/IDD-01-2023-0009.

Salahudeen, S.A., Lawan, F.I., Aliyu, Y., Abubakar, A., Aliyu, L., Rabiu, N., Ahmad, M., Shuaibu, A.R., Musa, A., 2024. HausaNLP at SemEval-2024 task 1: textual relatedness analysis for semantic representation of sentences. In: Ojha, A.Kr., Doğruöz, A.S., Tayyar Madabushi, H., Da San Martino, G., Rosenthal, S., Rosá, A. (Eds.), Proceedings of the 18th International Workshop on Semantic Evaluation (SemEval-2024). Association for Computational Linguistics, pp. 188–192. https://doi.org/10.18653/v1/2024.semeval-1.29.

Savci, P., Das, B., 2023. Prediction of the customers' interests using sentiment analysis in e-commerce data for comparison of Arabic, english, and Turkish languages. J. King Saud Univ. - Comput. Inform. Sci. 35 (3), 227–237. https://doi.org/10.1016/j.jksuci.2023.02.017.

Siddiqui, S., Zannou, O., Karim, I., Kasmiati, K., Awad, N., Golaszewski, J., Heinz, V., Smetana, S., 2022. Avoiding food neophobia and increasing consumer acceptance of new food trends-A decade of research. Sustainability (16), 14. https://doi.org/10.3390/su141610391.

Siegrist, M., 2020. Consumer acceptance of novel food technologies. Nat. Food. https://www.academia.edu/99862332/Consumer_acceptance_of_novel_food_technologies.

Siegrist, M., Hartmann, C., 2020. Consumer acceptance of novel food technologies. Nat. Food. 1 (6), 343–350. https://doi.org/10.1038/s43016-020-0094-x.

Siegrist, M., Sütterlin, B., Hartmann, C., 2018. Perceived naturalness and evoked disgust influence acceptance of cultured meat. Meat. Sci. 139, 213–219. https://doi.org/10.1016/j.meatsci.2018.02.007.

Singgalen, Y.A., 2022. Sentiment analysis on customer perception towards products and services of restaurant in Labuan Bajo. J. Inform. Syst. Inform. 4 (3). https://doi.org/10.51519/journalisi.v4i3.276. Article 3.

Song, Y.N., Oh, J., Chung, S., Cho, M.S., 2024. Consumer acceptance and perception of braised meat in soy sauce for older adults determined using fast profiling methods. Food Qual. Prefer. 120, 105249. https://doi.org/10.1016/j.foodqual.2024.105249.

Tao, D., Yang, P., Feng, H., 2020. Utilization of text mining as a big data analysis tool for food science and nutrition. Comprehens. Rev. Food Sci. Food Safe. 19 (2), 875–894. https://doi.org/10.1111/1541-4337.12540.

Teng, S., Khong, K.W., Sharif, S.P., Ahmed, A., 2020. YouTube video comments on healthy eating: descriptive and predictive analysis. JMIR Public Health Surveill. 6 (4), e19618. https://doi.org/10.2196/19618.

Terefe, N.S., 2022. Recent developments in fermentation technology: toward the next revolution in food production. In: Juliano, P., Buckow, R., Nguyen, M.H., Knoerzer, K., Sellahewa, J. (Eds.), Food Engineering Innovations Across the Food Supply Chain. Academic Press, pp. 89–106. https://doi.org/10.1016/B978-0-12-821292-9.00026-1.

Tsiourlini, M., Tzafilkou, K., Karapiperis, D., Tjortjis, C., 2024. Text analytics on YouTube comments for food products. Information 15 (10), 599. https://doi.org/10.3390/info15100599.

Tsvakirai, C.Z., Nalley, L.L., Tshehla, M., 2024. What do we know about consumers' attitudes towards cultured meat? A scoping review. Future Foods. 9, 100279. https://doi.org/10.1016/j.fufo.2023.100279.

Ulaga, W., Chacour, S., 2001. Measuring customer-perceived value in business markets: a prerequisite for marketing strategy development and implementation. Indust. Market. Manag. 30 (6), 525–540. https://doi.org/10.1016/S0019-8501(99)00122-4.

van Atteveldt, W., van der Velden, M.A.C.G., Boukes, M., 2021. The validity of sentiment analysis: comparing manual annotation, crowd-coding, dictionary approaches, and machine learning algorithms. Commun. Meth. Meas. 15 (2), 121–140. https://doi.org/10.1080/19312458.2020.1869198.

Vidal, L., Ares, G., Jaeger, S.R., 2022. Biterm topic modelling of responses to open-ended questions: a study with US consumers about vertical farming. Food Qual Prefer. 100, 104611. https://doi.org/10.1016/j.foodqual.2022.104611.

Waltz, E., 2022. Cow-less milk: the rising tide of animal-free dairy attracts big players. Nat. Biotechnol. 40 (11), 1534–1536. https://doi.org/10.1038/s41587-022-01548-z.

Watson, E., 2018. Perfect Day partners with ADM to commercialize animal free dairy proteins. Food. Navigator. USA. https://www.foodnavigator-usa.com/Article/2018/11/15/Perfect-Day-partners-with-ADM-to-commercialize-animal-free-dairy-proteins/.

Williams, L., Anthi, E., Burnap, P., 2024. A scalable and automated framework for tracking the likely adoption of emerging technologies. | EBSCOhost. https://doi.org/10.3390/info15040237.

Yamaguchi, T., Ezaki, K., Ito, K., 2024. Exploring the landscape of public attitudes towards gene-edited foods in Japan. Breed. Sci. 74 (1), 11–21. https://doi.org/10.1270/jsbbs.23047.

Yan, X., Guo, J., Lan, Y., & Cheng, X. (2013). A biterm topic model for short texts. *Proceedings of the 22nd International Conference on World Wide Web*, 1445–1456. https://doi.org/10.1145/2488388.2488514.

Yap, W.S., Murugan, P., Suntornnond, R., Choudhury, D., 2024. Commercial opportunities, future directions, and novel approaches to fermentation. In: Fraser, E.D.G., Kaplan, D.L., Newman, L., Yada, R.Y. (Eds.), Cellular Agriculture. Academic Press, pp. 343–357. https://doi.org/10.1016/B978-0-443-18767-4.00030-5.

Yousefi, N., Cakmak, M.C., & Agarwal, N. (2024). Examining multimodel emotion assessment and resonance with audience on YouTube. *Proceedings of the 2024 9th International Conference on Multimedia and Image Processing*, 85–93. https://doi.org/10.1145/3665026.3665039.

Zhen, L., Yabin, S., & Ning, Y. (2022). A short text topic model based on semantics and word expansion. *2022 IEEE 2nd International Conference on Computer Communication and Artificial Intelligence (CCAI)*, 60–64. https://doi.org/10.1109/CCAI55564.2022.9807822.