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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

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Abstract

Social media data are rapidly evolving and accessible, which presents opportunities for research. Data science techniques, such as sentiment or emotion analysis which analyse textual emotion, provide an opportunity to gather insight from social media. This paper describes a systematic scoping review of interdisciplinary evidence to explore how sentiment or emotion analysis methods alongside other data science methods have been used to examine nutrition, food and cooking social media content. A PRISMA search strategy was used to search nine electronic databases in November 2020 and January 2022. Of 7325 studies identified, thirty-six studies were selected from seventeen countries, and content was analysed thematically and summarised in an evidence table. Studies were published between 2014 and 2022 and used data from seven different social media platforms (Twitter, YouTube, Instagram, Reddit, Pinterest, Sina Weibo and mixed platforms). Five themes of research were identified: dietary patterns, cooking and recipes, diet and health, public health and nutrition and food in general. Papers developed a sentiment or emotion analysis tool or used available open-source tools. Accuracy to predict sentiment ranged from 33·33% (open-source engine) to 98·53% (engine developed for the study). The average proportion of sentiment was 38·8% positive, 46·6% neutral and 28·0% negative. Additional data science techniques used included topic modelling and network analysis. Future research requires optimising data extraction processes from social media platforms, the use of interdisciplinary teams to develop suitable and accurate methods for the subject and the use of complementary methods to gather deeper insights into these complex data.

Key words: Nutrition: Social media: Sentiment analysis: Emotion analysis: Data science: Natural language processing: Health and wellbeing

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Introduction

Poor nutritional status and the associated consequences such as the development of non-communicable diseases (NCDs) contribute to the overall global burden of disease[1]. Beyond the potential physical consequences, consuming a nutritionally poor diet has links to poor mental wellbeing and mental health[2,3]. To encourage the uptake of healthy eating behaviours, the environment in which people are influenced, including the physical built environment, social environment and the online environment, needs to make healthy eating the desirable and attainable option[4]. There has been increasing public dismissal of the credibility of nutrition information from experts[5,6]. People are alternatively using social media as a source of nutrition and health information[7,8] or motivation[9] and often trust this information more than expert sources[10]. Social media can be defined as 'web-based services that allow individuals, communities and organisation to collaborate, connect, interact and build community by enabling them to create, co-create, modify, share and engage with user-generated content that is easily accessible'[11]. Commonly, the people and accounts sharing nutrition information (often referred to as social media influencers) promote an idealised lifestyle and unrealistic body types and eating habits[12], such as following a restricted diet (e.g. keto, paleo or clean eating)[13]. Much of this information is not evidence based and does not follow dietary guidelines[14], consequently perpetuating misinformation and providing conflicting information about nutrition[15]. Additionally, this information is often being created by individuals without formal nutrition, dietetic or health qualifications[7] and is being spread through a range of distinct sub-communities on social media composed of people from a range

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of backgrounds[8]. As dietary advice varies by demographic and medical conditions, there is a benefit of sharing information within the specific sub-communities; however, it is not possible to predict how they interpret or act on this advice on social media. With little or no regulation of the content on social media around nutrition and food[16], it is imperative that evidenced-based information be amplified to counter the spread of misinformation and encourage healthy eating behaviours[14,17,18]. It is also important to understand the extent of the information that is being spread and the conversations that are being had on social media about nutrition and food to develop strategies to counter it and promote healthy eating.

Social media content (Table 1: Glossary of terms) from social media platforms such as Twitter, Instagram and Facebook, is one form of non-traditional real-time data that is being used in addition to, or as a replacement for, traditional research data collection methods such as randomised controlled trials, particularly to gather patients' perspectives[34]. Traditional research methods are costly, time consuming and burdensome on participants, whereas social media is habitually used by participants to express their opinions and its use in research can reduce the burden on both participant and researcher[34]. Social media usage is prolific, with approximately 70% of American adults[35], 56% of European adults[36] and 79% of Australian adults[37] using social media sites in 2018–2020. Behaviours, attitudes and perceptions of the public are readily available on social media and can be used to understand complex problems[11]. Social media has been previously used as a part of intervention studies which aimed at promoting and encouraging healthy eating[38,39]. Pre-existing social media data have been collected and analysed to investigate dietary behaviours[40] and to determine the types of social media posts and users who post that receive the most engagement by social media users[29,41]. Social media can also be used in real time for surveillance monitoring in areas such as disease outbreaks, medication safety, individual wellbeing and diet success[42]. However, previous research on social media in relation to nutrition has largely focused on output metrics of engagement online (e.g. likes, comments, shares) on a small scale (between nine social media profile pages and 736 social media posts) with use of manual analysis[8,14,29,41]. Nutrition research has less frequently explored large social media datasets and the breadth of the public's opinions and emotions expressed in social media posts.

Natural language processing (NLP) methods (Table 1) allow the analysis of large amounts of social media data to a deep level that goes beyond engagement and explores the opinions and 'real life' experiences of the social media users[43]. Social media data are often text based and written by human users, therefore comprising their 'natural language'. The number of social media posts about a certain topic and consequently the number of words in all those social media posts combined is vast. Thus, it is important to find a technique to analyse the data in a way that reduces time and human burden. Methods utilising NLP use computational techniques to learn, understand and produce human language content[26]. These NLP methods can use machine learning techniques (Table 1) to perform a range of textual analyses, such as tracking trending topics and identifying opinions and beliefs around different topics through topic modelling (Table 1) and identifying different social networks of people through social network analysis (Table 1)[26]. To gather social media information to be analysed through NLP techniques, the researchers need to mine or use web-scraping techniques to gather the data. This may be done through an application programming interface (API) (Table 1), which is a software intermediary that allows two applications to talk to each other in order to exchange information[19], and in this case gather social media data. These applications allow researchers to gather amounts of data that would be otherwise unavailable in large quantities or in an automated and efficient way[26].

One NLP technique that has been used to analyse opinions and attitudes on social media is sentiment or emotion analysis (Table 1). Sentiment or emotion analysis, sometimes referred to as opinion mining, uses written natural language to analyse the opinions, sentiments, attitudes and emotions embodied within the text[28]. Sentiment or emotion analysers can be based on machine learning or rule-based techniques. A machine learning approach typically uses either a subset of the sentiment or emotion coded text data, or a lexicon (Table 1) with words assigned to their corresponding sentiment or emotion, which is used to build and train a machine learning model to classify the sentiment of the text[28]. Other sentiment or emotion analysers use rule-based techniques or pattern libraries where patterns of sentiment and words are matched. Words and symbols within the natural language text are assigned a polarity, often on a scale of positive/very positive to negative/very negative. Sentiment or emotion analysis can be performed with a range of NLP and machine learning tools, from lexicon and rule-based tools such as Valence Aware Dictionary and Sentiment Reasoner (VADER) Sentiment[44], support vector machine algorithms[45] and Naïve Bayes algorithms[46] to models based on convolutional and deep neural networks[47] (for glossary of terms, see Table 1). Once the system for collection of data and analysis is set up, it can be a relatively quick way of interpreting large amounts of natural language data, typically tens of thousands or millions of posts, which would traditionally be a very time-consuming and labour-intensive process.

The use of sentiment or emotion analysis has increased with the popularity of social media, as social media data provide a never-before-seen amount of information about a range of different people's and communities' opinions, attitudes and experiences[28]. Sentiment or emotion analysis techniques are constantly evolving and have the potential to use the vast amount of nutrition- and food-related information that is present on social media, with over 113 million posts on Instagram using the hashtag #healthyfood as of 28 February 2023. Sentiment or emotion analysis helps to understand the sentiment and emotion behind the social media conversations in a consistent systematised way and to a scale that manual text or language could not achieve. Sentiment or emotion analysis provides another perspective beyond social media analytics by considering what was said about the topic. Sentiment or emotion analysis has been applied in many areas, including product or service reviews[48], politics and political events such as elections[49], healthcare[50] and health and wellbeing[51]. However, it is currently unclear how well sentiment or emotion analysis techniques that have been used in other contexts apply to nutrition and food and

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Table 1. Glossary of terms

Term	Definition
Application programming interface (API)	An intermediary connection between software or computer applications which allows the software applications to communicate with each other and exchange data[19].
Artificial intelligence	An area of study in the field of computer science involving the development of computers which can perform human-like thought processes such as learning, reasoning and self-correction[20].
Latent Dirichlet Allocation (LDA)	A generative probabilistic model which uses statistics to group words in a dataset into topics, where each topic in the dataset is characterised by a certain mixture of related words. LDA is a method used in topic modelling[21].
Lexicon	A type of dictionary used in natural language processing that contains information (semantic, grammatical, sentiment polarity) about individual words or word strings[22].
Linguistic inquiry and word count (LIWC)	A text analysis application and dictionary for studying the emotional, cognitive and structural components of verbal and written speech samples[23].
Machine learning	A data analysis method that is a branch of artificial intelligence where machines learn from and identify patterns in data and then make analytical model building decisions based on these learnings[24].
Naïve Bayes classifier	A probabilistic classifier based on Bayes' theorem used in machine learning, in which each feature (e.g. word in text) is assumed to make an independent and equal contribution to the probability of a sample to belong to a certain class (e.g. sentiment)[25].
Natural language processing (NLP)	Computational techniques used to learn, understand and produce human language content. NLP can use machine learning techniques to perform a range of textual analyses, such as tracking trending topics, identifying opinions and beliefs around different topics and identifying different social networks of people[26].
Recurrent neural network	Machine learning models which can be used in natural language processing based on the way computation works in the brain and characterised as learning through many layers of differentiable mathematical functions[27].
Sentiment analysis	Sentiment analysis (or opinion mining) uses written natural language to analyse the opinions, sentiments, attitudes and emotions embodied within the text. A machine learning technique where typically either a subset of the text data is coded to assign sentiment, or a lexicon with words assigned to their corresponding sentiment, is used to build and train a machine learning model to classify the sentiment of the text[28].
Social media	Web-based services that allow individuals, communities and organisation to connect, interact and build community by enabling them to create, co-create, modify, share and engage with user-generated content that is easily accessible[11].
Social media influencer	An individual, or group of individuals, who can shape attitudes and behaviours through social media channels. Can be a celebrity or someone that is unknown outside of social media[29].
Social network analysis	An analysis approach that involves theoretical concepts and analysis techniques to discover different social relationships between individuals or groups and the structure and influence of these social relationships[30].
Stemming	In natural language processing, the process of reducing words to their common base form, that is, eating would be stemmed to eat[31].
Supervised learning method	In sentiment analysis, method of classification involving training a model with a training dataset with pre-defined text with corresponding classification (e.g. sentiment) and then using this model to predict information (e.g. predicting sentiment). Support vector machines and Naïve Bayes Classifiers are examples of supervised learning methods[28].
Support vector machines (AKA support vector networks)	A machine learning method for learning tasks such as classification and regression, involving training a model with a training dataset and then using this model to predict information (e.g. predicting sentiment)[32].
Term frequency–inverse document frequency (TF-IDF)	A term frequency measure of the importance of terms in a document, with a larger weight given to terms which are less common in the dataset, lowering the importance of very frequent words[33].
Topic modelling	A natural language processing technique that uses a probabilistic statistical model to create topics based on related words within a dataset[21].
Unsupervised learning method	In sentiment analysis, classification based on some fixed syntactic patterns that are likely to be used to express opinions, for example a lexicon[28].

how sentiment or emotion analysis has been used to analyse nutrition and food related social media data. Therefore, the aim of this scoping literature review is to explore the use of the NLP technique of sentiment or emotion analysis to analyse social media content related to nutrition, food and cooking. The key objectives of this scoping review were to:

1. Classify the areas of nutrition, food and cooking that have been explored using sentiment or emotion analysis to assess healthy eating habits and dietary patterns.
2. Classify the techniques used to undertake sentiment or emotion analysis.
3. Determine the potential efficacy of using sentiment or emotion analysis on nutrition-, food- and cooking-related content.
4. Identify other data science techniques used alongside sentiment or emotion analysis and future research directions for sentiment and emotion analysis in the area of nutrition, cooking and food.

Methods

This systematic scoping review was conducted according to the updated Preferred Reporting Items for Systematic Reviews and

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Meta-Analyses (PRISMA) 2020 statement[52] and PRISMA extension for scoping reviews[53]. A systematic scoping review was chosen as a more appropriate method than a systematic review due to the aims of identifying the areas that the technique of sentiment analysis has been used in and to identify the key characteristics of the papers including the types of methods and outcomes[54]. Through initial searching, there were no previous literature reviews or literature review protocols identified with the same purpose related to nutrition, food and cooking social media sentiment analysis. Following the PRISMA statement and PRISMA extension for scoping reviews the scoping review was conducted using the following steps: (1) development of rationale and objectives; (2) determining eligibility criteria; (3) developing, testing and iterating a literature database search strategy; (4) screening papers for eligibility; (5) charting/extraction of the data; (6) synthesis of results. This review was registered with Open Science Framework (DOI: 10·17605/OSF.IO/2UW3E).

Inclusion and exclusion criteria

Types of studies. Quantitative and mixed-methods studies were considered for inclusion. Academic research in the form of journal articles and conference papers was considered eligible.

Types of intervention(s)/phenomena of interest. PICOTS was used to determine inclusion and exclusion criteria and subsequent search terms due to PICOTS often being used alongside PRISMA and in the area of nutrition. For PICOTS table for details on inclusion criteria, see Table 2. Studies which used sentiment and/or emotion analysis to classify sentiment or emotions of social media data related to nutrition, food and cooking were considered eligible. Sentiment analysis methods should involve computational classification of sentiment into different polarities (e.g. positive, negative and neutral) and not solely manual sentiment or emotion analysis. Data analysed in the studies must have been from a social networking (e.g. Facebook), media sharing (e.g YouTube, Pinterest), social news (e.g. Reddit), blogs and forums (e.g. Wordpress) or microblogging (e.g. Twitter, Tumblr) social media platform as defined by Sloan *et al.*[11]. The social media data needed to be related to nutrition, food, healthy eating or cooking.

Studies which looked at social media data related to food product, food delivery, restaurant or brand reviews and marketing of food were not included as they did not specifically relate to healthy eating or eating habits. Studies around weight loss, obesity or health conditions were not included unless they focused on a related diet or nutrition aspect as well. Social media data that focused solely on dietary supplements were not included. Studies which looked at social media data related to foodborne illness and food safety (e.g. genetically modified food and safety) were considered out of scope for this review. Papers had to be published in English. No date limit was applied.

Types of outcomes. To be eligible, papers could report outcomes related to the number or percentage of social media posts that were classified as different sentiments or emotions. If studies focused on the development of a sentiment or emotion analysis engine or method, eligible outcomes included the accuracy of that developed method to classify the sentiment or emotion of the social media data. Studies which included outcomes which compared the accuracy of multiple sentiment or emotion analysis methods were also eligible for inclusion.

Literature search strategy

Nine databases from both health and computer science were searched using the same search terms for relevant papers (Ovid MEDLINE, PubMed, Scopus, Emerald, INSPEC, Compendex, ACM Digital Database, IEEE and Computer Science Database) on 5 November 2020 and an updated search on 18 January 2022. These databases were chosen due to their coverage and popularity for use in both the areas of nutrition and computer science and as they contained key papers identified as eligible for inclusion from initial test searches.

Search terms included terms for sentiment analysis (e.g. 'sentiment analysis', 'sentiment classification', 'emotion analysis', 'opinion mining' combined with OR) AND terms related to social media (e.g. 'Social media', 'Social network*', 'Facebook', 'Instagram' combined with OR) AND terms related the nutrition and food (e.g. 'Nutr*', 'Healthy eating', 'Diet*' combined with OR). These search terms were chosen after multiple iterations to cover the three key aspects necessary for a paper to be included being: social media data, nutrition, food or cooking related and using sentiment or emotion analysis. Synonyms and related techniques for sentiment analysis were identified and test searches were used to see the scope and relevance of papers included using different terms. Searches were restricted to English language only. For the full search strategy, see Appendix 1.

Data management. Results from each of the databases were imported into Endnote. The Endnote file was then imported into Covidence software for duplicate removal, title and abstract and full text screening (Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia).

Data screening/study selection. Two reviewers (A.M. and E.J.) independently screened the titles and abstracts of each article for potential eligibility. The full text of those that were considered potentially eligible in title and abstract screening were independently screened by the same two reviewers (A.M. and E.J.). Any disagreement between the reviewers was either discussed until a consensus was reached or was resolved by a third reviewer (T.A.M.).

Data extraction

Data from each eligible study were extracted, charted and stored in an Excel spreadsheet (Appendix 2). The Excel spreadsheet used for data charting was developed and iterated on the basis of feedback from authors and from information that was presented in the included studies. Data charting was undertaken independently by the lead author (A.M.). Data extracted included details about the types of articles, author disciplines, aims of the study, social media platform, social media data extraction methods, amount of social media data collected,

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Table 2. PICOTS summary table

Population	Data from social media platforms related to nutrition, food or cooking
Intervention	Sentiment and/or emotion analysis
Comparison, control, comparator	Not applicable
Outcome(s)	Textual analysis of social media data: • Number or percentage of social media posts classified as each sentiment or emotion • Accuracy of sentiment engine to predict sentiment • Comparison of accuracy of different sentiment or emotion engines to predict sentiment or emotion • Other data science techniques used to analyse social media data
Timing	Not applicable
Setting	Social media platforms

sentiment analysis procedures, other analysis methods, results for sentiment analysis and other analyses and outcomes of significance to the research question of this review. Additionally, due to the research objective of identifying other data science techniques that can be used for social media data analysis in this area, data were extracted related to other analysis techniques used and the overall results of these analyses.

Data synthesis

A narrative synthesis was undertaken to summarise findings of the included studies. Quality appraisal was not conducted due to this being a systematic scoping review and of an exploratory nature, and therefore we were not evaluating the clinical effectiveness or assessing feasibility of an intervention[54].

Results

A total of 7325 papers were collected from the nine databases (Fig. 1). Of the 4303 papers included in title and abstract screening after duplicate removal, 4232 were considered irrelevant after first-pass screening. Papers that were excluded included those that used data from websites that were not social media platforms, papers focusing on health data that was not specifically nutrition, food or cooking related, papers which used other NLP methods but did not conduct sentiment analysis or papers that focused on specific food products and the marketing of those products. The full texts of seventy-one papers were screened, of which thirty-seven papers met the inclusion criteria and were included in the review. Papers that met most of the inclusion criteria but were not included overall, included papers such as by Pugsee *et al.*[56] that used data from a website that included comments of the recipes but would not be classified as a social media platform (as defined in methods) and Mazzocut *et al.*[57], who conducted manual analysis of sentiment rather than computational.

Characteristics of papers

Of the thirty-seven papers included, twenty-four were journal articles, ten were conference proceedings, one was a book chapter, one was a preprint publication and one was a technical report (Table 3). The results from one study were reported in both a journal article[86] and conference proceedings[85]. Characteristics of the papers can be found in Table 3. The authors of the papers were affiliated with a range of countries, with the most common including the United States ($n = 13$), followed by India ($n = 3$), Ireland ($n = 3$), Spain ($n = 3$), South Korea ($n = 3$), Algeria ($n = 2$), China ($n = 2$), Indonesia ($n = 2$), Japan ($n = 2$), Poland ($n = 2$), Czech Republic ($n = 1$), Iran ($n = 1$), Latvia ($n = 1$), New Zealand ($n = 1$), Portugal ($n = 1$), the Netherlands ($n = 1$) and the United Kingdom ($n = 1$).

Almost half ($n = 15$, 40·5%) of the papers had interdisciplinary authors from both health and computer science and technology fields, while sixteen (43·2%) had authors from only computer science/technology disciplines and four (10·8%) had interdisciplinary authors, however not including people with health backgrounds. The conference proceedings were primarily published by authors from computer science disciplines.

Characteristics of social media data

The majority of the papers ($n = 25$) used data from Twitter, followed by YouTube ($n = 7$) and blogs ($n = 3$). Less commonly used were Sina Weibo ($n = 2$), Facebook ($n = 1$), Instagram ($n = 1$), Reddit ($n = 1$), Pinterest ($n = 1$) and WhatsApp ($n = 1$). Papers primarily used one social media platform for all their data collection ($n = 32$), whereas five used a combination of platforms, often both social media and other websites (news sites, forums, PubMed). One study[64] identified Twitter users of interest and collected data from only those users, three papers collected comments from only the top YouTube channels in the area such as cooking[81,82,84], while others collected data through filtering posts using keywords that were relevant to their study.

The areas of nutrition, food and cooking covered across papers varied widely across five main themes and ten subthemes (Fig. 2). The first theme involved studies looking at dietary patterns including the four sub-themes of 'general dietary patterns and choices' including dietary preferences and attitudes ($n = 5$)[61,75,76,85,86], 'organic and sustainable food' ($n = 5$)[59,67,72,83,87], 'veganism' including both vegan diet and lifestyle ($n = 1$)[62] and 'gluten-free diet' ($n = 1$)[88]. The second theme involved 'cooking and recipes' ($n = 6$)[79–82,84,89]. The third theme involved 'diet and health' including the three sub-themes of diet and health conditions with the health conditions including general health status, diabetes and bowel disease ($n = 4$)[64,65,71,93], diet and obesity ($n = 2$)[90,94] and diet and weight loss ($n = 2$)[70,91]. The fourth theme involved public health including two sub-themes: public health policy and programmes in the areas of school meals, food security and sugar

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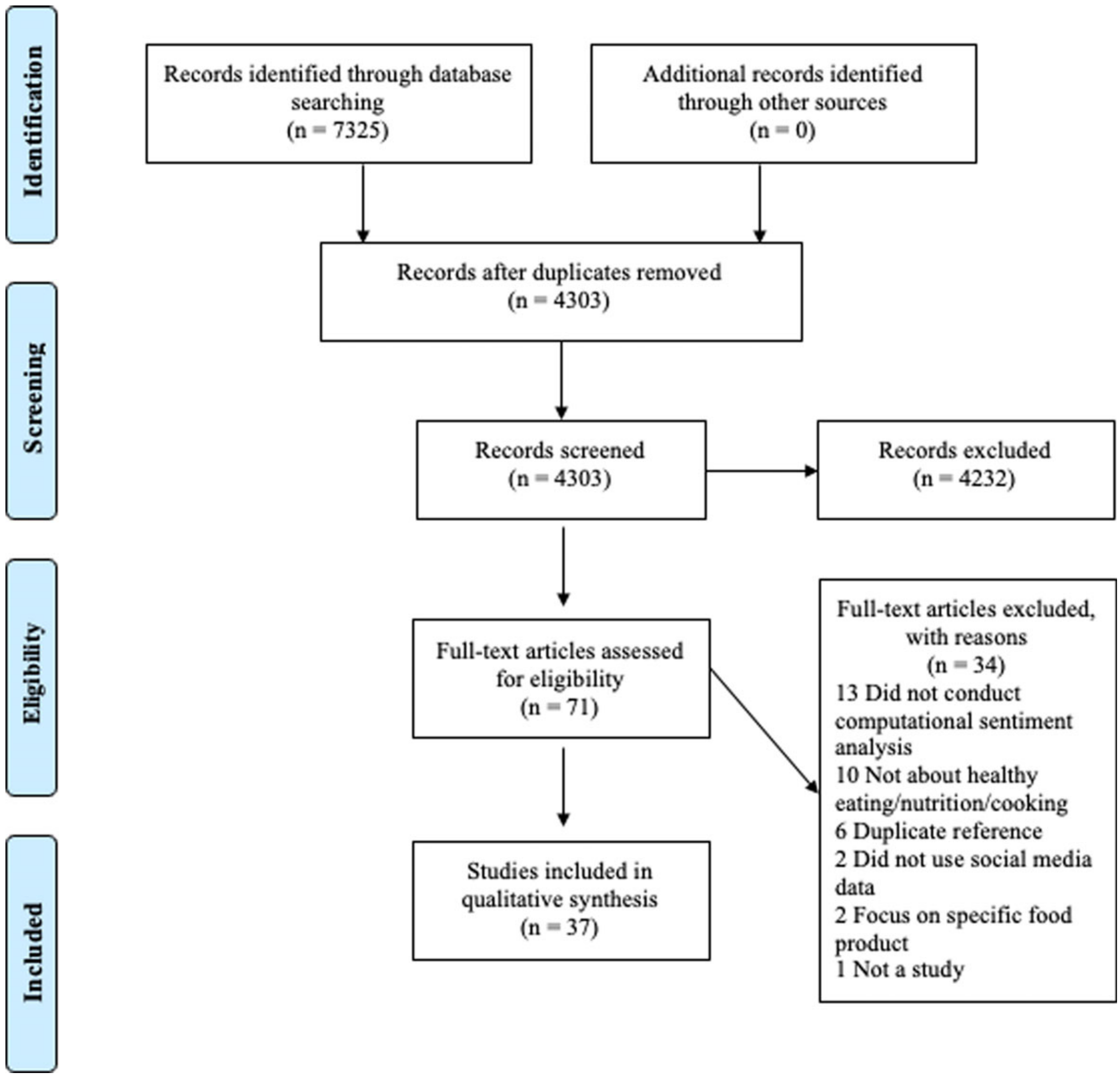

Fig. 1. PRISMA flow diagram of systematic scoping review on sentiment analysis and data science to assess the language of nutrition-, food- and cooking-related content on social media[55].

consumption ($n = 3$)[58,63,69] and food prices ($n = 1$)[74]. The fifth theme involved nutrition and food in general ($n = 6$)[66,68,73,77,78,92] including the sub-theme food and mood ($n = 1$)[60]. This theme also covered topics ranging from different health foods to diets, food trends and foods considered healthy and unhealthy. The papers in the cooking and recipes theme were all conducted using YouTube data and often used similar techniques or were by the same authors.

The aims and objectives of the studies varied widely and included: gathering social media users sentiment and opinions on their topic ($n = 15$)[62,63,68–70,72–76,85–88,92], building a sentiment classification system for their social media data ($n = 8$)[71,78,79,81,84,90,93,94], exploring their topic area and who is discussing it ($n = 6$)[58,59,65,66,77,83], understanding food consumption patterns and emotion ($n = 4$)[60,61,67,89] and building an online system or application to apply sentiment findings ($n = 1$)[91]. Other studies focused on developing a system to recommend recipes based on sentiment ($n = 1$)[80], monitoring health status ($n = 1$)[64] and exploring potential applications for machine learning in their topic area ($n = 1$)[82]. Those studies that focused on developing a methodology were more likely to build their own classification system than use an open-source tool, and their results were more likely to focus on testing of their model or framework rather than exploring what the data of their topic area were saying.

For those papers that used Twitter, the data were collected through either the Twitter API ($n = 12$, 48%) (Table 1), which uses archive Twitter data, or the Twitter Streaming API ($n = 6$), the live collection version of the API (Table 4). Other methods to extract Twitter data included the Decahose streaming API, which provides a random sample of 10% of all public Twitter messages. The YouTube API was used for all papers using YouTube. Social media data were collected primarily after 2010, with only three papers collecting data from before 2010. Data were collected within certain time periods; however, seven papers did not report the range of dates. Of those studies that

Table 3. Characteristics of studies by social media platform

Study	Data source	Country	Disciplines of authors	Type of article	Theme discussed
Twitter					
Bridge *et al.* 2021[58]	Twitter	United Kingdom	Business; Population Health; Psychology	Journal article	Sugar tax
Brzustewicz *et al.* 2021[59]	Twitter	Poland	Marketing; Economic Sciences	Journal article	Sustainable consumption
Dixon *et al.* 2012[60]	Twitter	The Netherlands	Artificial Intelligence	Technical report	Food and mood emotional wellbeing
Dondokova *et al.* 2019[61]	Twitter	South Korea	Computer Engineering	Conference proceedings	Eating patterns and food choices
Jennings *et al.* 2019[62]	Twitter	The United States	Nutrition and Food; Mathematics and Statistics; Psychological Sciences	Pre-print	Veganism
Kang *et al.* 2020[63]	Twitter	The United States	Information Systems; Epidemiology and Environmental Health	Journal article	School meals policy for childhood obesity prevention
Kashyap *et al.* 2014[64]	Twitter	The United States	Digital Advertising; Computer Science	Conference proceedings	Health status
Pérez-Pérez *et al.* 2019[65]	Twitter	Spain, Portugal	Computer Science; Biomedicine; Computer Engineering; Biological Engineering	Journal article	Bowel disease
Pindado *et al.* 2021[66]	Twitter	Spain	Agricultural Economics; Business Administration	Journal article	Food trends
Rintyarna 2021[67]	Twitter	Indonesia	Electrical Engineering	Journal article	Organic food
Saura *et al.* 2020[68]	Twitter	Spain, the United States	Business Economics; Public Health	Journal article	Nutrition and diets
Scott *et al.* 2018[69]	Twitter	The United States	Social Science; Data Science	Journal article	Supplemental Nutrition Assistance Program
Shadroo *et al.* 2020[70]	Twitter	Iran	Computer Engineering; Information Technology; Diplomacy and Public Relations; Health Management and Economics	Journal article	Diet and weight loss
Shaw *et al.* 2017[71]	Twitter	The United States	Library and Information Science	Conference proceedings	Diet, diabetes, exercise and obesity
Singh *et al.* 2022[72]	Twitter	Poland	Marketing	Journal article	Organic food
Sprogis *et al.* 2020[73]	Twitter	Latvia, Japan	Computing; Engineering	Conference proceedings	Food (e.g. eating, tasting, breakfast, lunch, dinner etc.)
Surjandari *et al.* 2015[74]	Twitter	Indonesia	Industrial Engineering; Economics	Journal article	Staple food prices
Vydiswaran *et al.* 2018[75]	Twitter	The United States	Health Science; Information Technology; Public Health; Computer Science and Software Engineering	Conference proceedings	Dietary patterns and attitudes concerning food
Vydiswaran *et al.* 2020[76]	Twitter	The United States	Health Science; Information Technology; Electrical Engineering and Computer Science; Health Management and Policy; Nutritional Sciences; Epidemiology; Statistics; Urban and Regional Planning; Health Behaviour and Health Education	Journal article	Dietary choices and attitudes
Widener *et al.* 2014[77]	Twitter	The United States	Geography; Geospatial Analysis and Computation	Journal article	Healthy and unhealthy food
Yeruva *et al.* 2017[78]	Twitter	The United States	Computing and Engineering	Conference proceedings	Healthy and unhealthy food; social contextual influences on healthy eating
YouTube					
Benkhelifa *et al.* 2018[79]	YouTube	Algeria	Computer Science and Information Technology	Conference proceedings	Cooking
Benkhelifa *et al.* 2019[80]	YouTube	Algeria	Computer Science and Information Technology	Book chapter	Cooking
Donthula *et al.* 2019[81]	YouTube	Ireland	Computing	Journal article	Cooking
Kaur *et al.* 2019[82]	YouTube	Ireland	Computing; Food Science and Environmental Health	Journal article	Cooking

Table 3. (*Continued*)

Study	Data source	Country	Disciplines of authors	Type of article	Theme discussed
Meza *et al.* 2020[83]	YouTube	Japan	Human Sciences	Journal article	Organic and local food
Shah *et al.* 2020[84]	YouTube	Ireland, India	Computing; Food Science and Environment Health; Information Technology	Journal article	Cooking
Sina Weibo					
Zhou *et al.* 2017[85]	Sina Weibo weibo.com	China	Information Management; Information Processing	Conference proceedings	Dietary preferences
Zhou *et al.* 2018[86]	Sina Weibo weibo.com	China	Information Management	Journal article	Dietary preferences
Instagram					
Pilař *et al.* 2018[87]	Instagram	Czech Republic, the United States	Economics and Management; Business	Journal article	Organic food
Reddit					
Rivera *et al.* 2016[88]	Reddit	New Zealand	Statistics; Computer Science	Conference proceedings	Gluten-free diet
Pinterest					
Cheng *et al.* 2021[89]	Pinterest	The United States	Health administration and policy; Health and Human Services; Communication; Nutrition and Food	Journal article	Nutritional content of recipes
Multiple platforms					
Kim *et al.* 2017[90]	Blogs, social network services, online news sites and online bulletin boards	Korea	Nursing & Systems Biomedical Informatics; Health and Social Affairs	Journal article	Diet and obesity
Kim *et al.* 2019[91]	Twitter and an online weight management community	South Korea	Computer Science and Engineering	Conference proceedings	Weight management
Masih 2021[92]	Twitter, YouTube, online news, blogs, magazines, press release, TV/radio and Vkontakte	India	Engineering management	Journal article	Health foods including organic, non-genetically modified, gluten-free, dairy-free and keto
Ramsingh *et al.* 2018[93]	Twitter, Facebook, blogs and WhatsApp	India	Computer Applications	Journal article	Food habits, physical activity and diabetes mellitus risk factors
Yeruva *et al.* 2019[94]	Twitter and PubMed	The United States	Computing and Engineering	Journal article	Obesity and healthy eating

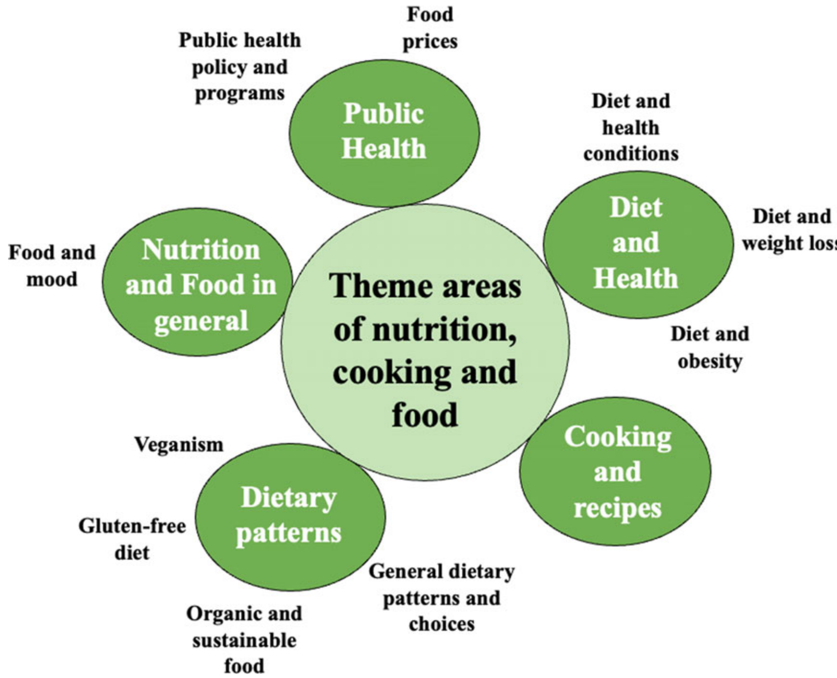

Fig. 2. Themes and sub-themes of topics across studies.

reported dates, the timeframe in which social media data were collected ranged from a 5-d period to a 9-year and 4-month-long period. Data were collected from a specific location in seven papers, the United States[63,69,77,78], China[86] and India[93], with other papers not specifying a location or focusing on social media across the world. Some papers collected only data that were published in a specific language, including English[60,62,63,65,68,70–72,83,91], Hinglish (Hindi/English)[81,82], Marglish (Marathi/English) or Devanagiri[84] and Latvian[73], while others did not specify.

Only seven papers reported how many unique social media users contributed to the body of social media data they collected, with these studies collecting data from either Twitter or Instagram[63–65,70,75,76,87]. The number of unique contributors ranged from 120 to 355 856 users and averaged across papers, 133 670 users contributed to the final samples of included data. Papers that used Twitter used between 700 and six million tweets that had been filtered for relevance and cleaned for data analysis (819 791 tweets on average across papers). Papers that researched YouTube commentary used between 1065 and 42 551 comments from videos (11 144 comments on average across papers).

Characteristics of sentiment analysis

The techniques used to classify the sentiment of the social media text data can be found in Table 4 (for glossary of terms, see Table 1). Techniques for sentiment analysis used included various Naïve Bayes/Bayesian methods ($n = 7$), support vector machines ($n = 5$), VADER ($n = 6$), decision trees ($n = 3$), linguistic inquiry and word count (LIWC) ($n = 3$), the Syuzhet package ($n = 3$), neural networks (multi-layer perceptron, recurrent) ($n = 2$), random forest ($n = 2$) and logistic regression ($n = 2$). Some papers used open-source sentiment software packages, that is, VADER[65,67,69,78,89,94], SentiStrength[83], CoreNLP[94], Sentiment140[60], PHPInsight[70], TextBlob[94], MeaningCloud (an Excel plug-in)[58] and an open-source model developed previously by Colnerič *et al.*[91,105]. Six papers[58,64,73,79,80,88] employed manual sentiment classification to verify a subset of the classifications or to provide training data for the sentiment classification method. Classifications varied between manual analysis, with Bridge *et al.*[58] finding 64% of their tweets being negative through MeaningCloud computational analysis compared with 52% through manual analysis.

Papers either used currently available sentiment analysis techniques as they are, modified versions of currently available techniques or created new techniques or algorithms for use in their study (Table 4). Thirteen papers[64,69,73,74,79–82,84,88,92–94] used a combination of methods, which they compared to ascertain their accuracy and the most appropriate method to use for their topic area and type of data (Table 4). Five studies[73,74,81,82,84] compared different word embedding and vectorisation techniques (for pre-processing of the data, see Table 1) alongside different sentiment classification techniques, while the others just looked at different sentiment classification techniques. Four papers[81,82,84,93] used term frequency–inverse document frequency (TF-IDF) (Table 1) to vectorise words within the social media text, which is a pre-processing step to assign words a number on the basis of its frequency in the dataset in order to analyse the data.

There were four papers which focused on the development of a sentiment classification technique and therefore reported only the efficacy of the different methods they developed such as the recall, precision and *F*-measure for predicting the sentiment of the text rather than reporting the actual proportion of text classified into the sentiment categories[79,81,82,84]. Accuracy

Table 4. Social media data collection, sentiment analysis techniques and key findings by social media platform

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Twitter							
Bridge *et al.* 2021[58]	This study aimed to explore the influence of actors (i.e. users on Twitter), the network (i.e. connection of actors) and conversations (i.e. what actors are talking about) involved in sugar sweetened beverage SSB tax debates on Twitter.	Twitter using NodeXL	5 August 2017 to 7 May 2019 (1 year, 9 months); 5366 gathered and 220 used for manual sentiment analysis	Using NodeXL collected tweets that contained the search term '#SugarTax' or tweets that were posted in response to the tweets with '#SugarTax'	• Sentiment was assessed using MeaningCloud an Excel plug-in • A sub-set of tweets were also analysed manually	Comparison of the sentiment assessed through MeaningCloud and those assessed manually	Sentiment analysis results: • Negative tweets automatic assessment using MeaningCloud, $n = 141$, 64%; compared with manual assessment, $n = 115$, 52% Other results: • Social network analysis: $n = 1883$ users, including members of the public, health campaign groups, professionals, food industry and food retail. Those that were most connected were spread widely throughout the network • Thematic analysis: Key themes in support of the sugar tax included negative health benefits of sugar and need for government intervention. Themes in opposition included ineffectiveness of the tax, increase in artificial sweeteners and individual responsibility for health
Brzustewicz *et al.* 2021[59]	The aim of this article is to identify which topics in the area of sustainable consumption are most important to consumers in the time of COVID-19.	Twitter streaming API using R	28 June to 12 July 2020 (2 weeks); 13 635 tweets after duplicates removed	Using Twitter streaming API collected tweets containing the term 'sustainable consumption'. Duplicates removed and parts that did not have meaning, i.e. URLS	Using the Syuzhet package[95] for sentiment which utilises the NRC lexicon to classify tweets into 8 categories: anger, fear, sadness, anticipation, disgust, joy, surprise and trust as well as positive and negative sentiments	Not applicable	Sentiment analysis results: • Positive sentiments most prevalent discussing sustainable consumption • Sentiment scores highest to lowest: positive, trust, joy, anticipation, negative, fear, surprise, anger, sadness, disgust • Words most associated with positive sentiment included: healthy, mindful, delicious, abundance, recovery, protect • Words associated with negative sentiment included: toxic, irresponsible, guilty, waste, loss, degradable Other results: • Topic modelling: Most prevalent topics included 'organic food consumption', 'food waste' and 'vegan food' • Sematic analysis: the central word consumption was connected with energy, electricity, environmental, lifestyle, responsible, reduce etc. The other central term, sustainable, was connected with food, carbon, energy, fuel, capitalism, etc.

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Dixon *et al.* 2012[60]	To gain a better understanding of global food consumption patterns and its impact on the daily emotional well being of people against the backdrop of country data such as Gross Domestic Product (GDP) and obesity levels	Twitter using Twitter API	Not reported	Querying the Twitter API with search terms such as 'for dinner', 'for lunch', 'for breakfast', 'I ate' and 'I'm eating'. System which gathers live data by continuously querying API	• Used a method similar to the technique created by Go *et al.*[96] using a distant supervised learning approach to classify sentiment • Used the Bayesian chance as a 'happiness percentage'	Not applicable	Sentiment analysis results: • The majority of the tweets had a positive sentiment, with certain foods having peaks in positive sentiment at different times (e.g. chocolate at Easter) • Countries with an average body mass index in the obese category and the healthy category both had positive sentiment around high-fat and high-sugar foods and fast foods • The positive sentiment of meat was high in many countries (over 70% positive) Other results: • 58% of the fifty most tweeted about foods globally were energy-dense nutrient-poor foods • Country-specific food was often classified into the country's top happiest foods list
Dondokova *et al.* 2019[61]	To describe and analyse the content of tweets in order to capture individuals' eating patterns and food choices.	Twitter using Twitter API	January to March 2018 (3 months); approximately 30 000 tweets with keywords from total 101 313 tweets from the time period with 59 177 left after removal of repeated tweets	Selection of keywords from the literature related to eating patterns and food choices (not specified what these were)	• Used a list of opinion lexicons created by Hu and Liu[97] based on customer reviews to classify polarity of tweets mentioning eating situations	Not applicable	Sentiment analysis results: • References to emotions were found in more than 50% of the food-related tweets • Positive sentiment: breakfast 44·8%, lunch 45·6%, dinner 51·6% and snacks 41·3% • Negative sentiment: breakfast 13%; lunch 12·4%, dinner 10·7% and snacks 13·2% Other results: topic modelling • Food types: more 'heavy' foods rather than 'light' foods (e.g. vegetables) were mentioned at lunch and dinner. Chicken was the most frequently mentioned food (4% of lunch and dinner tweets). Red meat, pork, seafood, hot carbohydrates and alcohol were more frequently mentioned at lunch and dinner. Most popular snack foods mentioned were snack bars, chocolate and fruit • Location: most commonly mentioned in relation to mealtimes not snacks. Places mentioned restaurants, school, home etc. • Social context: some tweets related to dinner referenced family

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Jennings *et al.* 2019[62]	To determine the perception of veganism portrayed on social media, and how this may differ or resemble what peoples' perceptions of veganism are outside of social media.	Twitter using Decahose streaming API (provides a random 10% of all public messages)	9 September 2008 to November 2015 (7 years, 1 month); approximately 5 million tweets	A sub-sample of the Decahose stream was used with tweets that mentioned the search terms 'vegan'	• Hedonometer algorithm used to classify sentiment which has happiness scores (from 1 to 9) for the 10 000 most frequently used words in the English language • Amazon's Mechanical Turk was also used to score happiness for 5000 of the most frequent words	Not applicable	Sentiment analysis results: • The daily happiness score for tweets which contain the word 'vegan' were on average higher (6·3 out of 9) than the average daily happiness score of all tweets (6·0 out of 9) • World Vegan Day appeared to be a day which scored higher for happiness • Tweets around veganism (both positive and negative) that were re-tweeted frequently by other users led to higher/lower happiness score around the time of the popular tweet
Kang *et al.* 2017[63]	To investigate the public's opinions on a new school meals policy for childhood obesity prevention, discover aspects concerning those opinions, and identify possible gender and regional differences in the U.S.	Twitter using Twitter API	9 February 2010 to 31 December 2015 (5 years, 10 months); 14 317 tweets after removal of duplicates from 11 715 Twitters users	Two lists of keywords and hashtags related to school meals policy for childhood obesity prevention. Keywords related to origin and name of the policy (e.g. Let's Move and USDA) and words related to the nature of the policy (e.g. child obesity, school meal, food policy)	• An unsupervised, lexicon-based approach was used to calculate a positive and negative value for each tweet based on previous work by Paltoglou *et al.*[98] • Utilises linguistic inquiry and word count (LIWC) look-up table, which has a pre-defined negation and intensifier word list for sentiment	Not applicable	Overall sentiment analysis results: • Sentiment of all tweets: 16·8% negative, 12·9% positive and 70·3% neutral • The ratio of positive/negative compared with neutral tweets increased from 2010 to 2015 • Average positive-to-negative ratio was lower for female (0·677) than for male (0·717) • Average positive-to-negative ratio was greater for the South United States (0·82) and the Midwest United States (0·81) than the West United States (0·74) and the Northeast United States (0·71) Sentiment results for different aspects of the tweets: • Source: first-hand: 67·5% positive; 71·6% negative versus second-hand: 32·5% positive; 28·4% negative • Target: campaign: 51·3% positive; 39·2% negative versus food: 32·5% positive; 54·2% negative versus other: 16·2% positive; 6·6% negative • Function: statement: 57·1% positive; 70·8% negative versus question: 20·4% positive; 12·1% negative versus agreement: 25·0% positive; 17·1% negative

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
							• Holder: student: 4·6% positive; 8·8% negative versus health professional: 2·9% positive; 0·0% negative versus parent: 1·7% positive; 0·4% negative versus media: 1·7% positive; 1·2% negative versus retailer: 0·4% positive; 0·0% negative versus school staff: 0·0% positive; 0·8% negative versus food producer: 0·8% positive; 0·0% negative versus unidentified: 87·9% positive; 88·7% negative
Kashyap *et al.* 2014[64]	To leverage social media data to monitor general user health.	Twitter using Representational State Transfer (REST) API	March 2014 (1 month); total of 120 Twitter users were sampled, with over 100 tweets per user	API call GET returns a set of tweets from the targeted users which included: dieticians, physicians, fitness gurus, twitter celebrities, IT professionals and followers, @burgerking commentors, @krispykreme commentors, #postpartumdepression mentioners, #crohnsdisease mentioners, general users	• Utilises the open-source Sentiment140 sentiment analysis tool • Also mapped emoticons to a certain polarity. • Four different approaches to classifying Twitter user health score based on sentiment polarity which were verified with manual annotation of a sub-sample	Difference between average health scores calculated with algorithm versus human: Dietitian tweets: algorithm 3·06; human 2·84 @KrispyKreme tweets: algorithm 1·74; human 1·62	Sentiment analysis results: Based on Twitter users' 'Health score' from their sentiment discussing health-related topics: • Dietitians: 'healthy' 85·7%; 'neutral' 14·3%; 'unhealthy' 0% • Doctors: 'healthy' 46·1%; 'neutral' 23·1%; 'unhealthy' 30·8% • Fitness gurus: 'healthy' 86·7%; 'neutral' 0%; 'unhealthy' 13·3% • Tech and entrepreneur: 'healthy' 50%; 'neutral' 35%; 'unhealthy' 15% • Celebrities: 'healthy' 73·3%; 'neutral' 16·7%; 'unhealthy' 10% • General: 'healthy' 0%; 'neutral' 13·3%; 'unhealthy' 86·7% • @BurgerKing: 'healthy' 60%; 'neutral' 0%; 'unhealthy' 40% • @Krispy Kreme: 'healthy' 0%; 'neutral' 20%; 'unhealthy' 80% • #PostpartumDepression: 'healthy' 40%; 'neutral' 0%; 'unhealthy' 60% • #CrohnsDisease: 'healthy' 20%; 'neutral' 0%; 'unhealthy' 80%

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Pérez-Pérez *et al.* 2019[65]	To characterise the bowel disease (BD) community on Twitter, in particular how patients understand, discuss, feel, and react to the condition.	Twitter using Twitter API	1 February 2018 to 31 August 2018 (7 months); 24 634 tweets by 13 295 different users	The Java library Twitter4J was used to filter tweets by search terms such as inflammatory bowel disease, irritable bowel disease, irritable colon, ulcerative colitis, ileocolitis, ileitis, Crohn, granulomatous, and jejunoileitis	• Valence Aware Dictionary and sEntiment Reasoner (VADER)[44] API for Python was used for classifying sentiment based on the compound score of each word in the tweet	Not applicable	Sentiment analysis results by semantic category *n* (%): • Disease (*n* = 10 538 tweets): negative 5691 (54·00%); neutral 1686 (16·00%); positive 3161 (30·00%) • Symptom (*n* = 1719): negative 1152 (67·02%); neutral 103 (5·99%); positive 464 (26·99%) • Food and diet (*n* = 2772): negative 1303 (47·01%); neutral 222 (8·01%); positive 1247 (44·98%) • Drug (*n* = 658): negative 237 (36·02%); neutral 118 (17·93%); positive 303 (46·05%) • Treatment (*n* = 1614): negative 710 (43·99%); neutral 339 (21·00%); positive 565 (35·01%) Other results: • The most used terms were associated with disease (35·64%, 11 688/32 794) and food and diet (25·43%, 8342/32 794)
Pindado *et al.* 2021[66]	The aim of this study is the identification of food trends geolocated communities, defined here as dense groups of people broadcasting information and opinions about innovative food trends (i.e. any food-related concept implying novelty) and the characterisation of their attitudes towards this topic as a pillar of its social representation.	Twitter API through R software and twitteR package	11 January to 31 January 2016 (3 weeks); 18 911 tweets collected. 7014 tweets after cleaning	The twitteR package allowed for collection of tweets containing ‘new foods’. Only tweets up to 1 week before the search can be collected, so several searches were conducted to gather more tweets	Dictionary-based approach using ‘Syuzhet’ dictionary[95], using the ‘sentimentR’ package on R. SentimentR considers contextual valence shifters of the sentences in the tweets when calculating the average sentiment score	Not applicable	Sentiment analysis results: • Overall sample had a weak positive sentiment towards food trends with a mean sentiment score of 0·320 (SD 0·251) • Sentiment score varied widely amongst different geographical regions; however, all scores on average were positive • The lowest mean scores were for Lagos (Nigeria) mean 0·183 (SD 0·136) and Nigeria mean 0·219 (SD 0·167) • The highest scores were for Malaysia mean 0·74 (SD 0·165) and Pretoria (South Africa) mean 0·442 (0·254) • Both the North American and European clusters had a low positive attitude, all with similar scores (mean of around 0·30) Other results: • Likelihood-ratio tests showed users within a spatial community were more similar to each other than to different communities

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Rintyarna 2021[67]	The aim of this study is to provide more recent, yet time saving analysis about the purchase decision pattern of Indonesian consumer especially under Covid-19 Pandemic situation.	Twitter API through the OAuth Package for R	Not reported	Using OAuth for R to authenticate a link to the Twitter API to collect tweets with the hashtag #makananorganik (Food organic)	PHP Sentiment Analyzer package that employs VADER[44]. To use in the context of Indonesian language the Inset lexicon was used which contains Indonesian language; 3609 positive words and 6609 negative words	Not applicable	Sentiment analysis results: • Overall 64% positive tweets. Exact numbers of negative and neutral sentiment not reported • Positive tweets often discussed organic food in relation to 'kesehatan' (health), 'praktis' (practical) and 'diet' • Negative tweets often related organic food as expensive • Most frequent words associated with sentiment (from most to least frequent): (1) 'Kesehatan' health (positive); (2) diet (positive); (3) 'Makanan' (neutral); (4) 'Praktis' practical (positive); (5) 'Mahal' expensive (negative)
Saura *et al.* 2020[68]	To identify the main topics and their sentiments (positive, negative and neutral) that provide meaning to the concept of healthy diet in the UGC in Twitter for which a data mining and topic modelling process was developed.	Twitter using Twitter API	9 April 2019 to 23 April 2019 (2 weeks); 14 731 tweets collected 10 591 tweets for analysis after cleaning	Tweets which contained the keyword #Diet or #FoodDiet in the hashtag	• Using text data mining to train a sentiment analysis algorithm in Python, to divide the data into segments expressing positive, negative and neutral sentiments • They identified 379 samples of training data related to healthy eating and diet • They then applied this algorithm to each topic area	Not applicable	Sentiment analysis results: Weighted percentage (WP) of sentiment for each topic (created through LDA topic modelling): • Diseases: WP 4·49 (negative); healthy food: WP 4·32 (positive); sugar: WP 3·18 (negative); fruit and vegetables: WP 3·13 (positive); proteins: WP 3·05 (neutral); carbohydrates: WP 2·93 (negative); ketogenic: WP 2·47 (neutral); healthy habits: WP 2·39 (positive); processed food: WP 2·13 (negative); bodybuilding: WP 2·09 (positive); vegans: WP 1·68 (neutral) Reliability of sentiment analysis conclusions (average Krippendorff's α value): • Positive sentiment: 0·759 ('tentative') • Negative sentiment: 0·798 ('tentative') • Neutral sentiment: 0·691 ('tentative')

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Scott *et al.* 2018[69]	To explore public opinion on the Supplemental Nutrition Assistance Program (SNAP) in news and social media outlets, and track elected representatives' voting records on issues relating to SNAP and food insecurity.	Twitter using Twitter Streaming API	May 2017 to June 2017 (2 months); 700 tweets	StreamR package for R used to access the Twitter Streaming API and search for search terms related to the Supplemental Nutrition Assistance Program including 'SNAP', 'food stamp', 'food stamps' and 'EBT'	• For the Twitter data the scikit-learn package from Python was used to undertake supervised sentiment classification • The study also collected news articles that were analysed using VADER[44] sentiment analysis and using the AFINN sentiment lexicon	Comparing VADER and AFINN for news article sentiment: Both methods had high correlation for classification; however, it was common for AFINN to score a text excerpt as negative when VADER scored it as positive	Sentiment analysis results: • Results based on news articles: there was a strong correlation between extreme sentiment classification (positive or negative) and extreme media bias Other results: • This study created an online sentiment analysis tool for social media and media outlets data (yet to be released publicly) which provides visualisations (interactive word clouds) of how the Supplemental Nutrition Assistance Program is discussed and changes over time
Shadroo *et al.* 2020[70]	Aims at understanding tweets stated on the amount of reception shown by people in the course of weight loss in a period of 1 month.	Twitter using Twitter API	27 December 2017 to 30 January 2018 (1 month); 2 684 858 tweets collected from 545 524 Twitter users and 1 673 559 tweets from 355 856 users were eligible	A filter was placed on the collected tweets to include keywords #health, #diet, #fitness, #weightloss, obesity, weight lose attempt, weight loss journey	• The open-source software PHPInsight with the Sentiwordnet 3·0 dictionary[99] was used to determine negative, neutral or positive attitudes of the tweets • Three numerical scores were assigned to each tweet for positive, negative and objective (neutral) and the maximum score was considered the overall sentiment of that tweet	Not applicable	Sentiment analysis results: • Sentiment analysis overall: 57·1% neutral, 30·7% positive, and 17·1% negative • Percentage of tweets per topic: no topic 0·1%; diet 20·6%; gym 11·5%; disease topics 1·2%; fundraising 0·2%; motivation 57·1%; obesity 9·4% • Tweets related to diet had slightly more positive than negative sentiment Number of twitter followers in each topic by sentiment • Diet: 3939 positive, 3554 neutral, 3719 negative; gym: 5290 positive, 5079 neutral, 3391 negative; disease: 5002 positive, 5118 neutral, 4021 negative; fundraising: 5187 positive, 4249 neutral, 5161 negative; motivation: 4670 positive, 6524 neutral, 3277 negative; obesity: 6723 positive, 7403 neutral, 8445 negative

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Shaw *et al.* 2017[71]	This study proposes a new framework to analyse unstructured health related textual data via Twitter users' post (tweets) to characterise the negative health sentiments and non-health related concerns in relations to the corpus of negative sentiments; regarding Diet Diabetes Exercise, and Obesity (DDEO).	Twitter using Twitter API	1 June 2016 to 30 June 2016 (1 month); approximately 6 million tweets	Real-time data were collected for tweets that contained the search terms for different topics: #diabetes OR diabetes; #diet OR diet; #exercise OR exercise; and #obesity OR obesity	• Used a lexicon-based tool, linguistic inquiry and word count (LIWC) to identify negative sentiments from the text in the Twitter data	Not applicable	Sentiment analysis results of different topics (topic modelling using LDA): • Diet: negative sentiment around medication, types of diets (i.e. skinny diet, vegan and juicing) • Diabetes: negative sentiment around genetic causes of obesity • Exercise: negative sentiment towards biking, sports and running and mental health • Obesity: negative sentiment toward body weight, weight loss and medical fads for weight loss Other results: Sub-topics: • Diet: food; fast food; medications; wellness; alternative diets; religious diets; sweets • Diabetes: obesity; hypertension; kidney; cancer; food • Exercise: lifestyle; weightless; body image; diet; mental health • Obesity: diet; diabetes; medical; cancer; weight; food • Non-health topics: people; emotions; celebrity; government; events
Singh *et al.* 2022[72]	The objective of this study is to identify the topics that users post on Twitter about organic foods and to analyse the emotion-based sentiment of those tweets.	Twitter streaming API using Tweepy for Python	10 January 2021 to 7 March 2021 (2 months); 43 724 collected and 41 009 tweets after duplicates removed	Tweets in English containing the keyword 'organic food' were collected through Tweepy, a Python library to access Twitter API	NRC Emotion Lexicon was used which assigns words with eight emotions (joy, trust, fear, surprise, sadness, disgust, anger and anticipation) and two sentiments (positive and negative). 'Syuzhet' package[95] was used to score the emotion and sentiments	Not applicable	Sentiment analysis results: • Organic food tweets were mostly positive • Frequent positive words were: 'eat', 'healthy', 'safe', 'fascinating', 'aroma', 'perfect', 'vitality' and 'delicious' • Frequent negative words were: 'junk', 'unnatural', 'fake', 'waste', 'doubt', 'ridiculous' and 'unbelievable' • Emotions (highest to lowest frequency): trust, joy, anticipation, fear, sadness, anger, disgust, surprise Other results: topic modelling • Topic significance ranking: (1) plant-based diet; (2) authenticity; (3) seasonality; (4) organic farming and standardisation; (5) saving the planet; (6) US politics (Capitol attacker's demand for organic food); (7) food delivery; (8) US politics (Attack on Capitol Hill)

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Sprogis *et al.* 2020[73]	We describe the Twitter eater corpus (TEC) and analyse its contents. We also provide two sub-corpora - one consisting of question and answer tweets and one with sentiment-annotated tweets.	Twitter using Twitter API	October 2011 to April 2020 (8 years, 6 months); 2 275 787 tweets collected, with 1 297 159 tweets mentioning foods or drinks	To track relevant tweets 363 keywords were used, which are various variations of Latvian words related to eating, tasting, breakfast, lunch, dinner, etc.	• Conducted manual annotation of sentiment for a subset of the data to train the sentiment analysis classification • Compared a Naïve Bayes classifier from the NLP toolkit[100] using Python, with Pinnis'[101] implementation of the Perceptron classifier, as well as comparing different combinations of training data sets from previous studies	Comparison of sentiment classification techniques: Highest sentiment classification accuracy of 61·23% was achieved by using the Naïve Bayes classifier, all training datasets except for Kudo *et al.*[102] and only stemming words (not conducting lemmatisation)	Sentiment analysis results: • Overall sentiment of tweets: *n* = 1631 positive, *n* = 2507 neutral and *n* = 1282 negative Other results: • Mention of specific foods peaked during different times such as mentions of buckwheat during panic buying at the start of the COVID-19 pandemic and horsemeat during a scandal in 2013 • Most mentioned food (in descending order): chocolate, ice cream, meat, potatoes, salads, cake, soup, pancakes, sauce, apple • Most mentioned drinks: tea, coffee, juice, water, beer, cocktails, Coca-Cola, alcohol, champagne, vodka
Surjandari *et al.* 2015[74]	To examine public sentiment analysis of staple foods price changes on twitters data.	Twitter using Scraperwiki	14 April 2014 to 1 June 2014 (2 months); Not specifically reported. Data from results approximately 18 348 tweets	Scraperwiki and online tool to scrape data from multiple online sources and put into a database, was used to collect tweets related to staple foods in Indonesia. Exact search terms not specified	• Training data with tweets labelled as positive or negative was then analysed by machine learning algorithms to train the classification model • Compared differences in accuracy between different models (support vector machine, Naïve Bayes and decision tree) and stemming words	Comparison of accuracy of the sentiment classification techniques: Naïve Bayes: with stemming 65·76%; without stemming 72·23% SVM: with stemming 75·19%; without stemming 80·35% Decision tree: with stemming 53·99%; without stemming 54·22%	Sentiment analysis results: • Total positive: 4235; total negative: 14113. • Chicken: positive 555, negative 1882 • Orange: positive 212, negative 561 • Cooking oil: positive 111, negative 104 • Kerosene: positive 5, negative 46 • Salt: positive 57, negative 81 • Maize: positive 436, negative 480 • LPG: positive 196, negative 784 • Sugar: positive 394, negative 689 • Cayenne: positive 1088, negative 526 • Rice: positive 645, negative 803 • Red onion: positive 84, negative 1305 • Beef: positive 267, negative 3714 • Milk: positive 24, negative 411 • Egg: positive 161, negative 2727 • Butter: positive 0, negative 0

Table 4. *(Continued)*

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Vydiswaran *et al.* 2018[75]	We extend prior work by investigating tweet contents that reveal attitudes concerning food.	Twitter using Twitter API, Twitter Gardenhose stream and through Twitter user timelines	2007–2015 (8 years); 28·83 million tweets collected, 1·34 million tweets considered eligible from over 153,000 Twitter users	Food-related terms (3928 food-related keywords) were used to mine the tweet content. Keywords were compiled from multiple online sources including foods from the USDA website, Wikipedia pages and list of restaurant chains	• Analysed sentiment by counting the number of food-related sentiment words • Used an expanded version of the linguistic inquiry and word count dictionary[23] to include food-specific sentiment terms • Sentiment score was computed by normalising the number of sentiment words with the number of words overall in the tweet	Not applicable	Sentiment analysis results: • Overall: 435 954 (79·2%) positive and 114 606 (20·8%) negative • There were 1 017 315 food words mentioned – 694 502 (68·3%) were unhealthy food words, while 322 813 (31·7%) were healthy food words Sentiment by healthiness classification (based on healthy and unhealthy food words): • Positive sentiment: healthy tweets 113,214 (79·3%); unhealthy tweets 144 975 (74·3%) • Negative sentiment: healthy tweets 29,533 (20·7%); unhealthy tweets 50 056 (25·7%)
Vydiswaran *et al.* 2020[76]	To assess discussions related to a specific topic (i.e., diet) at a highly localised level (i.e., a census tract, roughly equivalent to a neighbourhood). Furthermore, we aim to mine social media data at large enough scale that our sample is representative of social media users in the neighbourhood.	Twitter using Twitter API, Twitter Gardenhose stream and through Twitter user timelines	2014–2016 (2 years); 21 188 997 tweets from 120 748 users collected, 1 338 265 tweets from 88 030 users contained food key words	Food-related terms (3928 food-related keywords) were used to mine the tweet content. Keywords were compiled from multiple online sources including foods from the USDA website, Wikipedia pages and list of restaurant chains	• Same sentiment classification method as Vydiswaran *et al.* 2018[75]	Not applicable	Sentiment analysis results: Multivariate regression of sentiment by healthiness of tweets against neighbourhood measures: • Affluence, disadvantage and race were significant in the model for healthy and unhealthy tweets • Age was significant but only for unhealthy tweets • Affluence index was inversely correlated with overall sentiment score • Neighbourhoods with a higher percentage of African Americans had more positive sentiment Other results: key themes from content analysis • Behaviour: eating or drinking $n = 445$ (28·9%); cooking or preparing food $n = 98$ (6·4%) • Attitudes (positive): affection for food or food establishment $n = 177$ (11·3%); craving $n = 101$ (6·4%); enjoying food and drink $n = 127$ (8·3%) • Attitudes (negative): dislike for food or food establishment $n = 26$ (1·6%); struggles with food (overeating, discomfort after eating) $n = 19$ (1·2%) • Locations: coffee shops $n = 86$ (5·5%); locations: restaurants $n = 150$ (9·5%)

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Widener *et al.* 2014[77]	1. Introduce a new framework for exploring health-related social media data that employs sentiment analysis at a large scale based on the acquired big spatial data, 2. Analyse the overall spatial distribution and sentiment of tweets on healthy and unhealthy foods, and 3. Explore the relationship between the locations of tweets on healthy and unhealthy food and USDA-designated food desert census tracts.	Twitter using Twitter Streaming API	26 June 2013 to 22 July 2013 (1 month); 500 000 tweets collected, 128 914 included in analysis	Tweets were filtered by geo-location in the United States and including keywords from a list of 93 healthy foods and 65 unhealthy foods	• Obtained sentiment from the actual food entity mentioned in the tweet rather than the tweet as a whole • Used Alchemy API, which extracts words that are related to subjectivity and opinions. Then a supervised classification technique was used to estimate the positive or negative orientation of the words	Not applicable	Sentiment analysis results: Sentiment and healthiness scores by low income, low access to healthy food (LILA) tract (0 indicates not LILA tract, 1 indicates LILA tract): • Healthy, negative tweets: LILA tract 0: $n = 12\,442$; LILA tract 1: $n = 1678$; total: $n = 14\,120$ • Healthy, positive tweets: LILA tract 0: $n = 23\,465$; LILA tract 1: $n = 2901$; total: $n = 26\,366$ • Unhealthy, negative tweets: LILA tract 0: $n = 37\,858$; LILA tract 1: $n = 5356$; total: $n = 43\,214$ • Unhealthy, positive tweets: LILA tract 0: $n = 57\,393$; LILA tract 1: $n = 7440$; row total: $n = 64\,833$. Other results: • Regression models: the more positive the tweet, the more likely that the tweet is about healthy food. Tweets in LILA tracts less likely to be about healthy foods • 73·6% of tweets in LILA tracts were about unhealthy foods, 72·7% in non-LILA tracts ($p < 0·05$)
Yeruva *et al.* 2017[78]	1. To develop a Big Data Analytics framework that analyses Twitter data for classification of food types and food sentiments, 2. To analyse the geospatial sentiment of tweets on healthy eating and map them onto the regions in the CDC's Obesity Prevalence Map 3. To explore the Deep Learning Analytics for food image classification to understand the social food trends and obesity.	Twitter using Twitter Streaming API	September 2017 (1 month); 1588 tweets	Real-time tweet data are collected that contains information about location and includes search terms from a list of 75 healthy foods and 37 unhealthy foods	• Used VADER[44] sentiment analysis tool to compute a compound score of sentiment for each word in the tweet • Neutral sentiment was grouped with the positive as they were looking for the negative and positive eating trends only	Not applicable	Sentiment analysis results: • Positive: $n = 1287$ 81%; negative: $n = 301$ 19%; healthy: $n = 342$ 22%; unhealthy: $n = 1246$ 78% • Unhealthy-positive: $n = 1002$ 63%; healthy-positive: $n = 285$ 18%; unhealthy-negative: $n = 244$ 15%; healthy-negative: $n = 57$ 4% Other results: • The South of the United States had the highest prevalence of obesity (32·0%), followed by the Midwest (31·4%), the Northeast (26·9%) and the West (26·0%) • The CDC obesity prevalence green region contained tweets with more healthy foods (e.g. spinach and broccoli) while the red region had more unhealthy foods (e.g. pizza and beer)

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
YouTube							
Benkhelifa *et al.* 2018[79]	To study the problem of short text special characteristics typically found on social media and to show how much it is important to consider these characteristics in the preprocessing phase.	YouTube using YouTube APIs 'Google developers'	May to August 2016 (4 months); 2000 YouTube comments	Cooking recipe names as search terms. Send requests to API by entering the cooking recipe name. Tool collects relevant URLs and comments of these videos	• Emoticons and injections bags of emoticons and injections used in comments with positive or negative sentiment • Support vector machine training model using manually annotated sentiment of a subset of training data to build sentiment prediction algorithm	Comparison of two algorithms: Algorithm 1: accuracy 83·5%; recall 0·835; precision 0·835; *F*-measure 0·835 Algorithm 2: accuracy 95·3%; recall 0·953; precision 0·953; *F*-measure 0·9535	Sentiment analysis results: Sentiment classification accuracy results of Algorithm 2 (more accurate algorithm): • Positive sentiment: recall 0·964; precision 0·944; *F*-measure 0·954 • Negative sentiment: recall 0·943; precision 0·963; *F*-measure 0·953 Opinion filtering classifier (classifying text as either 'opinion' or 'other'): • Version 1: accuracy 78·7%; recall 0·787; precision 0·787; *F*-measure 0·787 • Version 2: accuracy 93·4%; recall 0·935; precision 0·936; *F*-measure 0·9355 Objective and subjective text classifier (classifying text as subjective versus objective/ binary): • Subjective: recall 0·903; precision 0·963; *F*-measure 0·932 • Objective: recall 0·966; precision 0·909; *F*-measure 0·937
Benkhelifa *et al.* 2019[80]	To rank various cooking recipes in order to select the best one through the reviews and the meta-data (Likes, Dislikes, and the views) associated with each one.	YouTube using YouTube APIs 'Google developers'	Not reported	Cooking recipe names as search terms	• Emoticons and injections bags of emoticons and injections used in comments with positive or negative sentiment • Used both Naïve Bayes and support vector machine methods to develop six methods of classification with different algorithms related to the processing of emoticons and use of meta-data of the video (e.g. views, likes and comments) • Manual annotation of a subset of training data to build sentiment prediction algorithm	Comparison of six different sentiment methods: Naïve Bayes: precision 0·772; recall 0·749; *F*-measure 0·761 NB + Algorithm 3 + Algorithm 4: precision 0·929; recall 0·867; *F*-measure 0·897 Support vector machine: precision 0·896; recall 0·918; *F*-measure 0·907 SVM + Algorithm 3 + Algorithm 4: precision 0·948; recall 0·950; *F*-measure 0·949 SVM + meta-data: precision 0·944; recall 0·947; *F*-measure 0·946 SVM + Algorithm 3 + Algorithm 4 + MD: precision 0·969; recall 0·952; *F*-measure 0·961	Sentiment analysis results: Number (*n*) of positive and negative opinions in text related to different video aspects: • Duration: 1108 positive; 914 negative • Decoration: 963 positive; 898 negative • Difficulty: 968 positive; 1024 negative • Healthy: 1061 positive; 1352 negative • Cost: 1244 positive; 1197 negative • Taste: 1047 positive; 914 negative • Recipe: 2109 positive; 1634 negative Accuracy of different methods for extracting different video aspects: • Based on their lexicon using Semeval restaurant dataset: precision 87·9%; recall 92·3% • Based on their lexicon and their dataset: precision 94·2%; recall 94·7%

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Table 4. (*Continued*)

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Donthula *et al.* 2019[81]	To increase the performance of sentiment analysis of Hinglish comments by multi-label text classification on cookery channels of YouTube using Deep learning.	Already collected YouTube data from Kaur *et al.* 2019	Not reported; 9800 comments	Data collected from the two top YouTube cookery channels in India. 'Hinglish' comments collected from cooking videos from these channels	• Development of a machine learning model using a multi-layer perceptron neural network using different feature vectorisers such as count, term frequency inverse document frequency (TF-IDF) vectoriser, pre-trained embeddings and custom embeddings	Comparison of different models: Most accurate for YouTube channel 1: Count vectoriser: 3 layers, 15 neurons, Adam optimiser, tanh activation (accuracy 98·53%) AND 3 layers, 20 neurons, Adam optimiser, tanh activation (accuracy 98·53%) Most accurate for YouTube channel 2: TF-IDF: 3 layers, 20 neurons, Adam optimiser, tanh activation (accuracy 98·22%)	Sentiment analysis results: Accuracy results using multi-layer perceptron with the count vectoriser sentiment classification: • Hinglish comments on cooking YouTube channel 1: sentiment accuracy of 98·53% • Hinglish comments on cooking YouTube channel 2: sentiment accuracy of 98·48%
Kaur *et al.* 2019[82]	RQ1. Which machine learning classifier works best for classifying the Hinglish text? RQ2. What are the useful patterns in the viewers' comments? RQ3. What are the potential capabilities of using machine learning techniques in favour of Youtuber perspectives? RQ4. Do we find that the prospective digital approach supports the provider in the long run?	YouTube using YouTube API	March 2019 (1 month); 9800 comments	Data collected from the two top YouTube cookery channels in India. 'Hinglish' comments collected from cooking videos from these channels	• A machine learning model was built using different classification techniques and algorithms • Cross-validation was performed on the training data and the accuracy of the model was evaluated on the test data	Comparison of different techniques: YouTube channel 1: SVM linear kernel with the TF-IDF vectoriser had the highest accuracy of 73·74% and precision of 75·15% YouTube channel 2: Support vector machine linear kernel with TF-IDF vectoriser had the highest accuracy of 75·30% and precision of 76·56%	Sentiment analysis results: Most accurate sentiment classification model: • Hinglish comments on cooking YouTube channel 1: logistic regression with the term frequency vectoriser with 74·01% accuracy • Hinglish comments on cooking YouTube channel 2: logistic regression with term frequency vectoriser with 75·37% accuracy
Meza *et al.* 2020[83]	1. To find diffusion paths of local and organic food products on YouTube by collecting information on related videos and comparing their network levels with social network analysis. 2. To review trends and differences among discourses through framing analysis on video content. 3. To explore the opinions, attitudes, behaviors, and emotions expressed by viewers through semantic and sentiment analyses on comments extracted from the videos.	YouTube using YouTube API	2015 (1 year); 964 videos collected; 923 videos eligible. For sentiment analysis 1065 comments from 213 videos	YouTube API queries with the search terms 'organic food', 'local food' and 'local organic food'. Videos were manually tested for eligibility and random sample of comments made on 'average' videos were included in final sample	• The open-source SentiStrength software package was used to assign a sentiment value to the words and emoticons in the comments using technique based on Thelwall *et al.*[103]	Not applicable	Sentiment analysis results: • Comments on local organic food videos had a higher positive valence and was perceived as more human/social than 'organic' food ($p = 0·03$) which was more associated with health risks • There was no significant difference in negative valence between local and organic food videos Other results: • Network analysis: Local organic food videos had higher connected components, modularity, diameter and average path lengths in their network than organic foods and the local organic food videos were driven mostly by media and business YouTube channels

Table 4. *(Continued)*

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Shah *et al.* 2020[84]	RQ1. Will there be different categories but the comments present will be predominant in a category? RQ2. Which machine-learning algorithms can be applied to the dataset? RQ3. Among the different parametric and non-parametric models, which model will give the best result?	YouTube using YouTube API	Not reported; 42 551 comments were extracted, with 14 453 (Marglish) and 4145 (Devanagiri) comments eligible for analysis	The comments from the videos on the top Marathi Cookery Channels on YouTube were extracted. Comments were then filtered to include only Marglish and Devanagiri language comments	• Compared combinations of different machine-learning algorithms and vectorisation techniques at categorising sentiment • Different vectorisation techniques: TF-IDF vectoriser, Count vectoriser and Hashing vectoriser • Different machine-learning algorithms	For Devanagari language dataset: The Bernoulli Naïve Bayes algorithm with the Count vectoriser had the highest accuracy (60·60%). For Marglish language dataset: Multilayer perceptron algorithm with all the vectorisers (TF-IDF, Count and Hashing) had the highest accuracy, 62·28%, 62·68% and 60·93% respectively	Sentiment analysis results: • This study compared combinations of machine-learning algorithms and vectorisation techniques to best categorise sentiment for a Devanagari language dataset and a Marglish language dataset
Sina Weibo Zhou *et al.* 2017[85] and Zhou *et al.* 2018[86]	To analyse dietary preference of social media users based on microblogs.	Queries to retrieve related microblogs in Sina Weibo	January 2015 (1 month); collected 8 748 195 microblogs, 3 975 800 microblogs included after cleaning	Dish name keywords as queries in Sina Weibo which includes 25 675 dish names from meishijie website.	• An unsupervised learning method is used to identify if the text has the aspects of interest (e.g. food dish name, dietary preferences, taste and price related to food) • Use a sentiment lexicon to identify sentiment polarity of the text related to dietary aspects and dishes • Lexicon used was a combination of HowNet and NTUSD	Not applicable	Sentiment analysis results: Performance evaluation of sentiment classification for dish aspect and dish type: • Kappa coefficients: aspect sentiment 0·76; dish sentiment 0·72 • Aspect sentiment: Macro-Precision 0·7146; MacroRecall 0·7638; F1 0·7384; accuracy 0·9078 • Dish sentiment: Macro-Precision 0·7349; MacroRecall 0·7987; F1 0·7655; accuracy 0·7862 Correlation co-efficient between aspects sentiment and dishes sentiment: • Taste: 0·190 ($p < 0·01$); distance: 0·155 ($p < 0·01$); function: 0·135 ($p < 0·01$); atmosphere: 0·222 ($p < 0·01$); appearance: 0·125 ($p < 0·01$); price: 0·059 ($p < 0·01$); service: 0·068 ($p < 0·01$) Other results: • Dishes that were commonly mentioned were more likely to have a higher satisfaction value • Weibo users are most satisfied with taste, appearance and service, and the most unsatisfied with function of food. Their satisfaction values for the higher aspects were only 0·6

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Instagram							
Pilař *et al.* 2018[87]	1. To identify the perception of organic food using 1 325 435 interactions by 313 883 users on Instagram worldwide. 2. To identify the most commonly used hashtags on social networks related to the term "organic food" using social network analysis, as well as the dominant sentiments of Instagram users about organic food using sentiment analysis. 3. To compile a hashtag interconnection network and extract dominant communities.	Instagram using a script that indexes messages from users worldwide	4 July 2016 to 19 April 2017 (9 months); 1 325 435 messages from 313 883 users collected. 100 000 random messages chosen for analysis	The script records messages on Instagram that include the 'organic food' hashtag and puts these into a database	A Netlytic program module was used to analyse sentiment of adjectives using the Gee Whiz Labs Inc.[104] list of adjectives. Tweets are classified into one (or more) of the following categories: • Appearance, • Condition, • Negative Feelings, • Positive Feelings, • Shape, • Size, • Sound, • Time, • Taste, • Touch and • Quantity	Not applicable	Sentiment analysis results: Percentage representation of categories of comments from #organicfood sentiment analysis: • Positive feelings: 42·98% • Taste: 22·73% • Appearance: 13·58% • Touch: 5·1%; size: 4·46% • Feelings (bad): 2·97% • Quality: 2·47% • Time: 2·94% • Shape: 1·96% • Sound: 0·82%. Other results: Network analysis: Most communities overlapped with others (modularity score 0·3030). The most connected communities were 'healthy living' and 'healthy lifestyle'. The 'vegetarian' community overlapped with the most other communities, 'healthy living', 'clean eating' and 'healthy lifestyle'
Reddit							
Rivera *et al.* 2016[88]	1. To construct models that discriminate between those who support and oppose each topic. 2. To identify opinion shifts over time, if they are present. 3. To describe the contents of discussions occurring under each topic.	Reddit API	January 2007 to September 2014 (9 years, 4 months); for analysis of gluten-free diet posts: extracted: 32 816; used in analysis: 2416	Used their own R package to scan Reddit thread titles for relevance, extract and process data 'RedditExtractoR' using search terms related to gluten-free diet e.g. 'gluten' and search terms relevant to other topics vaccination and genetic modification	• Used a dictionary-based sentiment analysis based on work by Hu and Liu[97] and Rinker qdap package for R to classify opinions into 'for'/ 'against' • Used a gradient boosted model to automate annotation of posts into 'for'/'against' the topic. Dataset was trained and tested	Manual annotation into 'for'/ 'against' proxy for sentiment (gluten-free diet data): between the two annotators the inter-rater agreement was moderate with a Fleiss' kappa of 0·452	Sentiment analysis results: • Sentiment annotation results for gluten-free diet data: for/positive: $n = 210$; against/negative: $n = 135$; indeterminate: $n = 655$ Other results: • Topic modelling (LDA): discussions often based around coeliac disease, the misdiagnosis of coeliac disease, corporate involvement in gluten-free diets and also general conversations around diet • Conversations around gluten-free diets peaked in frequency around the time a study was released that concluded that non-coeliac gluten sensitivity may not exist • Approximately 15% of the users accounted for about 50% of all comments in the 'against' category. Approximately 15% of users accounted for around 30% of comments in the 'for' category

Table 4. *(Continued)*

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Pinterest							
Cheng *et al.* 2021[89]	First, we aim to examine the patterns of food ingredients and nutrients prescribed by recipes posted on Pinterest. Second, by employing both traditional content analysis and a natural language processing (NLP) technique, we sought to understand the factors that distinguish the most popular recipes among users.	Pinterest search engine on two new accounts with no search history	28 June to 12 July 2020 (2 weeks); 207 recipes collected and 2818 comments under those recipes	Searched the Pinterest search engine for keywords recipe, breakfast, lunch or dinner. All pins that were recipes, and included eating occasion, cooking method, cooking time, ingredients and nutrition information were manually collected	Used VADER[44] sentiment analysis tool using Python 3·6 to classify tweets into positive, neutral or negative by polarity	Not applicable	Sentiment analysis results: • Positive most common approximately 0·36, negative approximately 0·225 and neutral least common approximately 0·08 • Taste-related comments: 25·9% positive significantly higher ($p < 0·05$) than negative at 13·2% and neutral at 6·1% • Taste and complexity most important factors shaping sentiments Other results: • $n = 544$ comments (19·3%) of comments were classified as taste, $n = 225$ (8%) as complexity and $n = 84$ (3%) as health • As followers increased the amount of meat served decreased ($p > 0·05$) • Engagement with post increased with increasing sugar content until the third quartile where it decreased ($p > 0·05$) • More engagement with high-fat and high-calorie recipes and less engagement with high fibre ($p > 0·05$)
Multiple platforms							
Kim *et al.* 2017[90]	To develop and evaluate an obesity ontology as a framework for collecting and analysing unstructured obesity-related social media posts.	Blogs, social network services, online news sites and online bulletin boards using an automated software crawler (unspecified)	January 2011 to December 2013 (3 years); 1 441 939 postings on the internet and social media	Software crawler to search keywords of 'obesity' and 'diet' in 217 online news sites, 4 blogs, 2 social network services and 11 online bulletin boards	• Unclear method of sentiment analysis. Classified postings into positive, neutral, and negative sentiments to answer the research question 'How do individuals think and feel about the concepts of obesity and diet?' • Created an ontology for the study around diet and obesity	Not applicable	Sentiment analysis results: • Overall sentiment across data sources: neutral: 66%; positive: 22%; negative: 12% • Trends over time: 2011: 20% positive; 67% neutral; 13% negative; 2012: 21% positive; 66% neutral; 13% negative; 2013: 23% positive; 65% neutral; 12% negative Other results: • Keywords from positive comments included 'to prevent obesity' and 'to manage obesity,' 'successful diet' and 'healthy diet,' and 'helpful exercise' and 'effective exercise' • Keywords from negative comments included 'skinny fat' and 'super-obesity,' 'failed diet' and 'excessive diet,' and 'exhausted from exercise' and 'no time for exercise' • The ontology developed for this study around diet and obesity was suitable for collecting relevant data and analysing the sentiment of the data

Table 4. (*Continued*)

Study	Study aim(s) or objective(s) (verbatim from the papers)	Social media platform and data extraction technique	Date collected (time frame); Amount of data	Search terms/methods for extraction	Sentiment analysis technique used	Comparison of sentiment analysis techniques	Key findings
Kim *et al.* 2019[91]	To create a new weight management application to track and monitor users' emotion in addition to calories and workouts, and provide emotional support from a emotion-aware chatbot and recommendation for personalised weight goals to help users to achieve their weight loss goals more effectively.	Twitter and an online weight management community using Tweepy and open API for Python 3·6	6 January to 16 January 2019 (10 d); 17 735 tweets	Twitter search terms included #weightloss, #diet, #fitness or #health. Tweets with these hashtags were only collected if the content includes the word 'weight'	A recurrent neural network (RNN) based sentiment analysis was performed using an open-source model by Colnerič *et al.*[105]. This model classifies sentiment in the form of emotion with eight types of emotions defined by Plutchik[106]	Not applicable	Sentiment analysis results: • #fitness, #health and #weightloss tweets had the highest percentage of 'joy' emotion classification followed by 'trust' and 'surprise' • #diet tweets had a higher percentage of 'sadness' and 'disgust' and the lowest percentage of 'joy' • Low weight loss progress of between 0% and 25% (indicated from the weight management community) had a higher percentage of 'fear' compared with all other levels of weight loss progress
Masih 2021[92]	Main objective of the paper is to understand the perception of consumer using Big Data analysis so as to assist health food manufacturers to improve food products according to customer choices and preferences.	Talkwalker mining tool and Meltwater data crawler	Talkwalker: 15 September 2020 to 21 September 2020 (1 week); 11 600 conversations. Meltwater: August 2020; blogs 7914, Twitter 5484, reviews and forums 1927, YouTube 1649, Facebook 1556	Talkwalker: unclear, mining tool that requires a keyword Meltwater: unclear, data crawler that provides data from various social media platforms	Through the Talkwalker and Meltwater tools which have sentiment analysis functions	Talkwalker and Meltwater have different sentiment analysis functions. Were not directly compared with the same data as they themselves collected unique data	Sentiment analysis results: • Talkwalker: positive 38%, negative 19% • Meltwater: neutral 82%, positive 13%, negative 5% Other results: Talkwalker: • Top interest for organic food search: food and drink 26·2%, family and parenting 16·6%, fitness and health 9·4%, celebrities and entertainment news 8·8%, social media 7·9%, music and audio 7·8%, colleges and universities 6·7%, literature/books 6·3%, general education 5·8%, employment 4·5% • Data collected from the United States 50·5%, Malaysia 15%, Argentina 12·5%, the United Kingdom 5·5%, India 5·4% • Demographics: 50·8% female, 49·2% male; 44·3% 18–24 year olds, 44·4% 25–34 year olds, 9·4% 35–44 year olds; 98·3% English • Occupations: author/writer 20·5%, executive manager 13·5%, artist 11·6%, student 10·1%, musician 8·8%, journalist 8·8%, health worker 8·8%, entrepreneur 6·5%, kitchen staff 5·7%, engineer 5·7%

Table 4. (*Continued*)

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Ramsingh *et al.* 2018[93]	To analyse the sentiment of people and their behaviour (lifestyle, food habits) with respect to the Non-Communicable Diseases. The objective of the work is to Design and Develop an Integrated Big-Data Model and Analytical Framework to mine the people opinion about healthcare using social media data.	Twitter, Facebook, blogs and WhatsApp using social media APIs (Twitter API, Graph API, Google + API, REST API)	Not reported; 9 000 000 instances and 2 000 000 instances after pre-processing	Flume, a standard Big-Data tool, was used to extract data using the hashtags and keywords related to food, lifestyle and physical activity (e.g. junk food, beverages, walking, jogging, cycling and occupation)	• Created a Hybrid Naïve Bayes Classifier-Term Frequency-Inverse Document Frequency (NBC-TFIDF) classifier. The probability score for different sentiment is calculated on the basis of the weight assigned to each word in the sentence • Used a Map Reduce model of computation using different *n*-grams	Classification performance using *n*-grams: Uni-gram: average 0·675. Bi-gram: average 0·765. Tri-gram: average 0·635.	Sentiment analysis results: • Overall sentiment of food-related data: positive: 60%; negative: 30%; and neutral: 10% Percentage of food types by sentiment classifications: • Positive: rice 18·06%, baked food 15·5%, junk food 17·2%, high-carbohydrate food 18·11%, wheat 15·33%, Cola 4·13%, slice 21·1% • Neutral: meat 1·27%, green leaves 2·76%, slice 2·32% • Negative: rice cakes 1·24%, watermelon 2·53%, pizza 2·96%, honey 5%, egg 4·32%, kidney bean 3·68%, soda 1·45%
Yeruva *et al.* 2019[94]	Propose the Contextual Word Embeddings (ContWEB) framework that aims to build contextual word embeddings on the relationship between obesity and healthy eating from the crowd domain (Twitter) and the expert domain (PubMed).	Twitter and PubMed using Twitter Streaming API	15 January 2018 to 19 January 2018 (5 d); 123 447 tweets collected, 103 609 tweets after cleaning; 41 199 healthy foods related and 62 410 unhealthy foods related	Tweets that contained healthy/unhealthy food keywords (76 healthy foods and 28 unhealthy foods) and 10 diseases keywords. Food keywords from USDA and ChooseMyPlate, as well as unhealthy meals and restaurant related words	• Developed Assemble Sentiment Analysis (ASA) meta-model based on existing tools VADER[44], CoreNLP[107], and TextBlob[108] • ASA is a rule-based sentiment analysis tool that incorporates social embeddings to be able to increase the accuracy of sentiment classification	Comparison of accuracy of ASA model with VADER, CoreNLP and TextBlob: VADER: positive 74·52%; negative 71·4%; neutral 67·36% TextBlob: positive 69·0%; negative 60·35%; neutral 63·93% CoreNLP: positive 58·53%; negative 33·33%; neutral 45·75%. ASA model: positive 80%; negative 79%; neutral 75·25%.	Sentiment analysis results: • Healthy/positive: *n* = 25 268, 32·6% • Unhealthy/positive: *n* = 7917, 10·2% • Compound/positive: *n* = 5853, 7·5% • Healthy/negative: *n* = 5685, 7·3% • Unhealthy/negative: *n* = 31 364, 40·5% • Compound/negative: *n* = 1310, 1·69% • Total healthy: *n* = 30 953, 39·99% • Total unhealthy: *n* = 39 281, 50·75% • Total compound: *n* = 7163, 9·25% Other results: • Topic modelling (LDA): topics from Twitter were significantly different from PubMed. Dominant topics for Twitter were cancer, blood pressure, cure, treatment, eat and family • Co-occurrence analysis: among the top 20 food items mentioned, 7 healthy food items and 13 unhealthy foods items were mentioned together with the obesity and disease terms

API, application programming interface; ASA, Assemble Sentiment Analysis; LIWC, linguistic inquiry and word count; SD, standard deviation; VADER, Valence Aware Dictionary and sEntiment Reasoner.

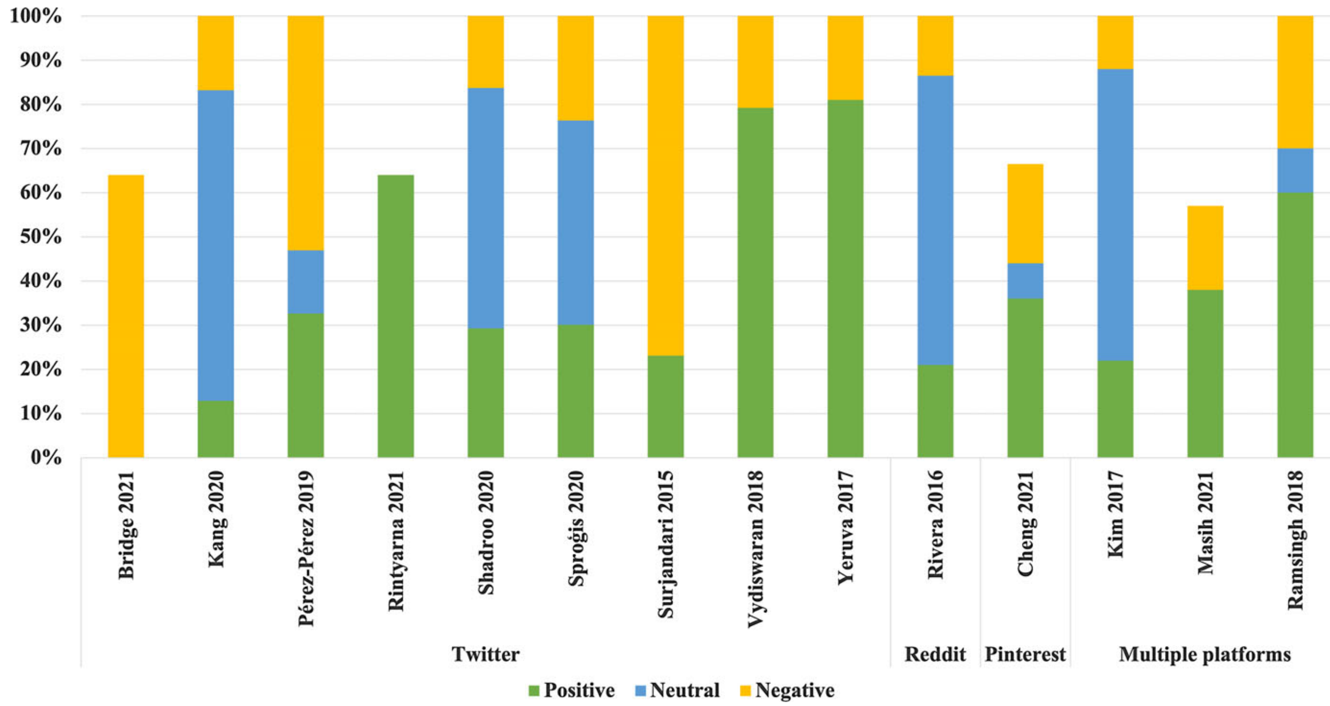

Fig. 3. Proportion of sentiment classifications (positive, negative, neutral) across studies by social media platform.

was reported in seven studies which often involved purpose-built machines and comparing multiple methods to ascertain the most accurate in their topic area[68,79–82,84,86]. Only one paper which used an open-source tool reported accuracy[94]. Across studies accuracy was on average 73·6%, while the accuracy ranged from 33·33% for predicting negative sentiment of obesity and healthy eating tweets using CoreNLP an open-source software[94] to 98·53% for predicting overall sentiment of cooking YouTube videos using a multi-layer perceptron neural network[81]. Neural network sentiment engines and support vector machines generally performed better than Naïve Bayes sentiment and decision tree sentiment engines.

Of the fourteen papers[58,63,65,67,70,73–75,78,88–90,92,93] that reported the percentage or amount of their overall data within each sentiment, the percentage of classifications ranged from 12·9% to 81% for positive (average across papers 38·8%), 8% to 82% for neutral (average across papers 46·6%) and 5% to 76·9% for negative (average across papers 28·0%); however, not all papers reported sentiment for all classifications (Fig. 3). Some papers had higher proportions of positive classifications either overall or by category, in topic areas such as food and mood[60], dietary patterns and choices[61,75], veganism[62], organic food[67,87], diet and health conditions[93], cooking[80] and nutrition and food in general[77,78], across Twitter[60–62,67,75,77,78], Instagram[87], YouTube[80] and multiple platforms[93]. Other papers had higher proportions of negative classifications in topic areas such as bowel disease and diet[65], diet and lifestyle as risk factors for diabetes[71], sugar tax[58] and food prices[74], all of which used Twitter data. Some had primarily neutral classifications in the topic areas of public health programmes[63], diet and obesity[90], gluten-free diet[88], diet and weight loss[70], health foods such as organic, non-GMO[92] and nutrition and food in general[73], across Twitter[63,70,73], Reddit[88] and multiple platforms[90,92].

Other analyses performed

Many of the papers looked at other NLP or machine learning methods alongside sentiment analysis, often to perform some form of analysis of subjective classifications of data. There were nine papers that classified the social media data by the healthiness or nutrition content of the food or subject of the text[64,68,75–78,80,89,94]. A health score was commonly based on a set of pre-defined 'healthy' and 'unhealthy' words or topics that the authors used to classify the health score of individual social media text entries[64,75–78,94]. Health scores were also assigned through topic modelling[68] or the classification of different aspects of a YouTube video, with 'healthy' being one aspect[80]. Health scores were sometimes used in combination with sentiment analyses, reporting sentiment classifications for 'healthy' and 'unhealthy' social media content (Table 4). Of those papers that reported a health score, neither the 'healthy' or 'unhealthy' text were consistently more likely to be positive, negative or neutral; however, more papers appeared to have a higher proportion of positive data overall for both 'healthy' and 'unhealthy' text. Other studies determined the nutritional content of the social media posts[68,89,93], for example analysing the nutritional content of recipes from Pinterest[89] and glycaemic index of food mentioned across a range of platforms[93].

Topic modelling was another NLP method used across fifteen papers[59,61,65,68–72,76,85,86,88,89,92,94] to statistically group the social media text data into different clusters with related words that commonly occur together to form topics. The most commonly

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used topic modelling technique was Latent Dirichlet Analysis (LDA) (Table 1), which was used across nine papers[59,68,70–72,85,86,88,94]. Emotion analysis which looks beyond positive/negative sentiment at the more nuanced emotion (e.g. joy, sadness, surprise) was performed in only three studies[59,72,91] with two of these studies[59,72] using the NRC lexicon, which is an open-source emotion analysis tool. Social network analysis[58,65,83] and clustering techniques[59,61,66,69,82,87–89] were used to explore relationships between and categorise the social media users or topics within the data. Other analyses performed included changes in the sentiment or topic of the social media data over time[62,65,70,73,88,90,92], with some studies considering world events at the time such as disease outbreaks, prominent discussions of the topic of interest in the media and food price increases[65,73,88], differences in sentiment or topic across different geo-locations[60,63,65,66,69,70,77,78,83,86,92] and gender differences[63,86]. As data were collected before and during the coronavirus disease 2019 (COVID-19) pandemic, there were three studies[59,67,73] which had some focus on the pandemic. Two of these studies[59,67] had mostly positive sentiment despite data being collected during the pandemic, and one study noted a peak in discussion of certain food groups during panic buying at the start of the pandemic[73].

Societal and practical implications of papers

All but two papers[64,81] discussed some broader societal and practical implications of their findings or their sentiment analysis techniques for future use in data science. These varied in detail and breadth, with more detail generally provided in papers including interdisciplinary authors. These implications included the following: gathering large-scale data using a platform consumers already use, discovering and being to monitor popular foods, eating habits and trends across time and across the world, and assessing public concerns and attitudes and the framing of the debate around issues such as public health policy. Other implications included being able to identify stakeholders and key influencers in different topic areas, detecting communities who discuss certain topics, understanding any common misconceptions around nutrition and understanding strategies to effectively communicate with your audience and encourage behaviour change that will be positively received.

Regarding issues such as ethics and privacy of social media data use, only three papers discussed ethics. One paper stated that YouTube data are publicly available so ethics approval to use the data was not required[83], another stating that while Twitter's data are publicly available they still sought ethical approval for their research[58] and another discussing not using verbatim tweet examples in the research due to ethical concerns[76]. Only three studies discussed privacy, with the discussion of the lack of personal information of the social media users such as gender and location due to privacy and data access policies of the social media platforms[63,85,86]. The potential for bias in the data or data analysis methods was discussed in ten papers. This included sampling bias of the people using social media to discuss this topic and how they did that (i.e. by using hashtags) versus non-users or people not discussing that specific topic[58,60,62,75–77], bias in the labelling of sentiment in the training data for the machine learning sentiment analyser[69,84], researcher bias in manual annotation of sentiment or topics and using multiple researchers to compare annotations to reduce this bias[58,63,88] and media bias (left versus right) and the corresponding sentiment[69].

Discussion

This systematic scoping review explored the academic literature related to the use of sentiment analysis of social media data in the area of nutrition, food and cooking. Of the thirty-seven papers that met the inclusion criteria, the range of nutrition related topics varied widely, including areas such as dietary patterns and choices, cooking, diet and health conditions, and public health policy and programme. Papers either focused on the development and methodology for creating a sentiment analysis tool for their respective topic of interest or used already available tools for sentiment analysis, sometimes modifying these to suit their needs. Only seven papers looked at the accuracy, precision or recall of the sentiment engine for their data to correctly identify the sentiment of the social media text. In general, using sentiment analysis on nutrition, food and cooking social media data helped with understanding of the data, but the efficacy of the techniques varied widely. The accuracy of the engine to predict sentiment across papers ranged from neural network engines having the highest accuracy of up to 98·53% to the open-source tool CoreNLP having the lowest accuracy of 33·33%. Alongside sentiment analysis, other analyses were conducted to gather further information on the social media text such as topic modelling, changes over time, network analysis and classification of the healthiness or nutrition content of the foods mentioned within the social media posts.

The included papers assessed a large range of nutrition-, food- and cooking-related topics, from attitudes of individuals in relation to their own eating to public health policy and programmes around nutrition. A previous review on sentiment analysis of health and wellbeing content found a similar variation in topics discussed, with their papers focusing on quality of life, cancer, mental health, chronic conditions, pain, eating disorders and addiction[51]. Gohil *et al.* found twelve healthcare-related papers using sentiment analysis in their review focusing on public health, emergency medicine and disease[50]. None of these papers in the previous sentiment analysis reviews on health and wellbeing[50,51] focused specifically on nutrition, cooking or food. The range of nutrition and health topic areas included in the current reviews and reviews by Zunic *et al.* and Gohil *et al.* speaks to the breadth of the area. However, this breadth and the particular nuances in language related to the specific topics (i.e. public health versus cooking) make it difficult to draw conclusions about the efficacy of using sentiment analysis in specific topic areas. The breadth of topics in nutrition science and health that have been covered in this review and previous reviews is dissimilar to other applications of sentiment analysis focusing on reviews and products. The review- and product-related data are generally more homogeneous, with the social media posts analysed all giving their opinions on the same topic[109]. This makes for greater comparability between papers, unlike in the

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current review when the topics and social media data were heterogeneous. Commonly, open-source sentiment analysis tools are trained using this homogeneous product review or unspecific social media data[50] and therefore may not be suitable for the specific nuanced language of nutrition and health social media data.

Across the current review and previous reviews on sentiment analysis in the areas of healthcare[50] and health and wellbeing[51], a range of different tools were used from purpose-built models using methods such as support vector machines, Naïve Bayes learning and decision trees to open-source freely available tools and commercial software. While the accuracy of purpose-built sentiment engines was more likely to be tested, the accuracy of open-source tools to predict sentiment for health-related topics is largely either unexplored or low. In the review by Gohil *et al.* on healthcare sentiment analysis, no papers applying open-source tools tested accuracy[50], and in the current review, accuracy was tested for only one open-source tool with a resulting accuracy of only 33·33%. Similar to the current review, accuracy was not routinely reported in reviews using sentiment analysis in the areas of health and wellbeing[51] and healthcare[50]. The accuracy of sentiment engines using purpose-built or modified tools such as support vector machines, Naïve Bayes classifiers and decision trees to predict sentiment of health and wellbeing data in a previous review on sentiment analysis was on average 79·8%[51], which was slightly higher than the average of 73·6% from the current review. These purpose-built or modified tools are more likely to be trained with data relevant to the topic area, making them more accurate; however, they require specialist computer science knowledge to create and run, so are not accessible to all. In comparison, the open-source tools are more accessible without specialist knowledge, but the lexicons used appear inappropriate for all topic areas. For example, the large lexical database WordNet, which is commonly used, does not include a general health, medical or nutrition domain[110]. This limits the benefit of using such open-source tools that are not altered for specific contexts, as they may be unlikely to capture the nuances in language and classify the sentiment of nutrition or health data appropriately. It is important that accuracy is measured when using a pre-built or open-source sentiment analysis method in a new context to ensure it a suitable method.

Sentiment analysis is an interdisciplinary field as it is used by and is optimised with the input from experts from linguistics, NLP, machine learning, computer science, psychology and sociology[111]. Specialist knowledge in the area of computer science and technology is critical to develop a sentiment tool that can be trained using pre-coded data from the topic area of interest. However, it is also important to have context and subject matter experts to assist with the development of the sentiment analysis methods due to the particular context and language used when discussing nutrition and health. In the current review, 40·5% of the papers had interdisciplinary authors from both health and computer science and technology fields. A previous review on social media analytics' use in nutrition found a third of papers had interdisciplinary authors; however, only two out of thirty-five papers involved authors from a nutrition background[40]. Of those interdisciplinary papers in this current review, the collaboration between nutrition subject experts and computer science allowed for the development of new ontologies or dictionaries specific to diet and obesity[90], cooking[82] and medical terms[88]. Two other papers used their interdisciplinary team to expand the previously existing linguistic inquiry and word count (LIWC) dictionary to include food-specific sentiment words that were relevant to their context[75,76]. Of the papers which were not multi-disciplinary in the current review, previously developed lexicons and dictionaries were most commonly used. However, to ensure that the word polarity of previously developed sentiment analysis tools is relevant to the new domain or topic of interest, cross-domain sentiment alignment is necessary[112]. To successfully apply sentiment analysis techniques developed by linguistics and computer scientists in healthcare, it is imperative that health professionals are also involved due to differing lexicons and interpretations of the sentiment of words from their different contexts.

Previous research using social media data by health professionals has often applied manual coding of content of the text and/or images of up to 5000 social media posts[29,40,41]. In the current review, only six papers[58,64,73,79,80,88] used a form of manual coding to verify a subset of the classifications or to provide training data for the sentiment classification method. Gohil *et al.*[50] previously found that six of twelve papers analysing sentiment of healthcare Tweets used a manual annotated sample and four of these used this sample to train their dataset. Manual classification has also been used as the sole sentiment analysis method in a study on nutrition as a complementary medicine by Mazzocut *et al.*[57], but was used on a smaller scale of only 423 data points. Sentiment analysis provides an opportunity to move beyond manual coding and to analyse previously unfeasible amounts of social media data in a systematic way and in much less time[28]. Humans have bias which is useful for applying context to the data with individual epistemologies and viewpoints, but this can make inter-rater reliability low when manually coding[113]. While not able to take into account some complexities of context and specificities in language, a sentiment analyser can be trained with relevant data to mostly accurately predict sentiment[28]. However, due to sentiment analysis models being trained with 'real-world' human social media data, they have biases towards what people typically say on social media[114]. For example, if a topic is generally discussed in a negative way, there would be more training data linking a negative sentiment to that topic and therefore the predicted sentiment for new data related to the topic would have a more negative sentiment score[114].

Sentiment analysis is rapidly evolving with constant improvements in the techniques and algorithms with developments in machine learning which will enhance accuracy of sentiment classification and the ability to apply these methods to different topics outside product reviews[115]. This rapid evolution makes for difficulties in generalising the applicability of sentiment analysis methods for future use, as a method that was useful 5 years ago may no longer be useful due to the constant changes and improvements, as well as the changes in social media. Additionally, being able to filter out inherent (direct or indirect) biases in the training datasets has been and will continue to be one of the biggest challenges in utilising machine learning techniques. Only ten out of the thirty-seven papers in this review

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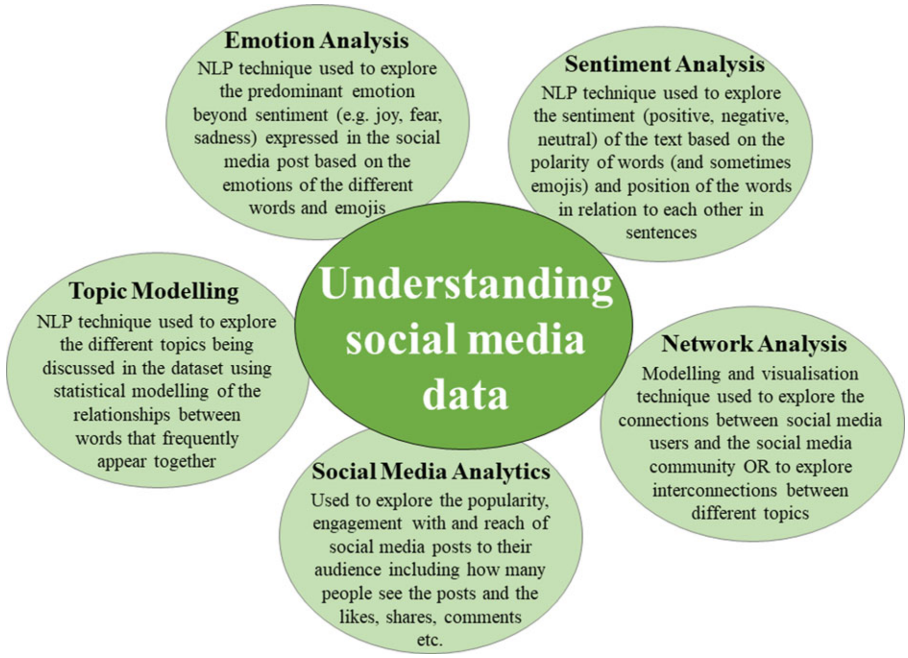

Fig. 4. An overview of social media data analysis techniques which were used across studies in combination with sentiment or emotion analysis to provide more nuanced insights into social media data.

discussed potential biases in the social media data themselves or the sentiment analysers and potential methods to overcome the bias. Today, there is much higher awareness of these potential biases, and new guidelines are being outlined to mitigate bias[(116)].

While it is useful to understand the sentiment of text to understand people's emotions behind differing topics, to gain a deeper understanding of the text data, other NLP and subjectivity analysis techniques (which include sentiment and emotion analysis) can be used in conjunction as well as quantitative social media analytics (Fig. 4). In this review, most papers did not just conduct sentiment analysis but also looked at other subjectivity analysis and NLP techniques such as topic modelling, topic evolution, sentiment evolution, emotion analysis and network analysis. Sentiment analysis is limited in its classifications usually on a three- or five-point scale for positive or very positive to negative or very negative[(28)], which may not be indicative of more complex emotions. Emotion analysis, which was conducted in only three studies in the current review, goes further than positive and negative to classifying text into, for example, eight emotions; anger, disgust, fear, joy, sadness, trust, anticipation and surprise on the basis of emotions defined by Plutchik[(106)]. Emotion analysis is considered more complicated than sentiment analysis but has been successfully performed using similar techniques to sentiment analysis, such as using a neural network[(105)] or other machine learning techniques. Topic modelling was the most commonly performed additional analysis which creates topics using probabilistic algorithm methods such as LDA. Topic modelling can be useful to group similar text-based data into themes to understand and summarise large text-based datasets in a more nuanced way and to explore the relationships between themes and changes over time through topic evolution[(117)]. Network analysis was also used in three papers[(58,65,83)], which is a useful way to explore relationships between social media users and how the content or people on social media discussing the topic are interconnected[(30)]. Those papers which focused on developing a sentiment analysis technique and comparing different algorithms for the most accurate prediction did not often conduct other analyses. Looking beyond sentiment resulted in a more in-depth view of the data, what topics were being discussed, changes in sentiment/topic over time and with different events in time and the community and the influencers that were discussing their topic.

Social media as a data source provides a unique view into unfiltered real-time conversations that are constantly evolving[(118)]. Because of its breadth in terms of topics, it is useful for exploratory and discovery research[(119)]. However, there are limitations to using social media as a data source for research. Social media platforms are not necessarily representative of the general population[(120)] or the data sample collected may not be representative of what is actually being said overall on the platform[(118)]. In this current review, Twitter was the most commonly used platform. Twitter and Facebook users have been found to be generally younger and with a higher education level than non-users and are more likely to be interested in politics particularly with more left-leaning political beliefs[(121)]. There are limitations in the ability to access certain data, with social media APIs having restrictions in the amount of data collected and sometimes being accessible only by organisations with partnerships with the platform or for a cost. Twitter has an accessible and free API, which may be a reason behind it being the most commonly used platform in this review and amongst previous research[(51)]. However, the Twitter API also has biases in what data you can retrieve as the Twitter Streaming API provides only a sample of the data to use[(118)]. The amount of data you can collect particularly using a free API is sometimes limited, with geo-location and

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other demographics of the users such as age and gender not always available as users have the option to switch precise location on or off, with the default being off[122]. Finally, it is important to note the potential ethical implications of using social media data, with only six studies in the review discussing ethics or privacy of social media data. While only publicly available social media posts are used and social media users agree to their data being used for research purposes through the user agreements, the users may not know exactly what their data are being used for[123]. There are potential risks to privacy and confidentiality and, therefore, it is imperative that careful consideration be taken to the ethical concerns of using these data[124] and that the potential benefits of the research outweigh any potential harm[125].

Limitations

Limitations of this review include not undertaking a quality assessment of the included papers as this was a systematic scoping review[54]. The study also included conference proceedings as they are widely used in the computer science field, as well as journal articles which differ in their reporting requirements and quality. However, some papers may have been missed due to the specific databases and search terms used. Only papers published in English were included, and therefore the results may be affected by information bias. We collected papers around nutrition, food and cooking broadly, and due to the heterogeneity in topics published in this area, there are limited conclusions about accuracy of using sentiment analysis in specific areas of nutrition. Both sentiment analysis and social media are rapidly evolving fields, and therefore the scoping review captures the area at only one specific point in time.

Recommendations for future research

On the basis of our experiences during the data extraction and synthesis of results, we recommend that future research utilising sentiment analysis, or more generally research on subjectivity analysis, could benefit from the following:

1. Interdisciplinary teams including those from computer science and subject-specific experts, especially subject matter experts, should be involved in the refinement of the sentiment lexicons and interpretation of the findings;
2. Development of specific sentiment or emotion lexicons related to the topic, as sentiment may differ for words from one topic to another (e.g. 'heart' having a neutral sentiment within a medical context while having a positive sentiment in a general context) and analysis of the accuracy of these sentiment analysis techniques with updated lexicons to predict sentiment in that topic area;
3. A combined use of subjectivity analysers and other techniques such as topic modelling and network analysis to gain a deeper understanding of the data and potential future implications using the data;
4. Clearer reporting of methodology including social media search terms used to retrieve data, date range of searches, procedures to mitigate bias in training datasets and discussion of ethical practice, particularly in relation to privacy; and
5. Consideration of the influence of world or local events on the social media conversation across specific date ranges and the change of conversations across time.

Conclusions

Social media data are useful to obtain a more nuanced understanding of what social media users are saying and sharing. However, research needs to go beyond traditional quantitative social media metrics such as likes and comments and incorporate a range of subjectivity analysis and NLP methods. Owing to the large volume of social media data, automated analysis techniques are needed. Sentiment analysis methods have been applied to nutrition-, food- and cooking-related content and had a relatively high accuracy rate for assessing sentiment (in the limited number of papers that assessed accuracy). The high accuracy rate was often due to the authors building their own algorithm which best suited the data, and therefore required expertise in computer science and technology. Open-source and publicly available sentiment analysis methods were used; however, papers which used them often did not test the accuracy of predicting sentiment or the accuracy was low potentially due to the lexicon used being based on a non-nutrition or health context. The meaning behind terms is often subject specific, and therefore subject matter experts (e.g. in nutrition) would make sure the textual data analysis is relevant to that topic. While it was shown sentiment analysis can be useful to analyse social media data, papers which used other NLP or machine learning techniques gained a more nuanced understanding of their data beyond sentiment. Interdisciplinary work is the key to successful implementation of machine learning, subjectivity analysis and NLP methods that are rigorous, accurate and relevant to the specific field (e.g. nutrition) and provide practical and societal implications of their findings.

Supplementary material

To view supplementary material for this article, please visit https://doi.org/10.1017/S0954422423000069.

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Conflicts of Interest

None declared.

Authorship

Annika Molenaar was involved in the planning of the review, search term development, database searching, assessment of papers for eligibility, data extraction and writing the article. Eva L. Jenkins was involved in the assessment of papers for eligibility and reviewing the written manuscript. Linda Brennan was involved in the planning of the review and reviewing the written transcript. Dickson Lukose was involved in reviewing the written manuscript. Tracy McCaffrey was the senior author involved in planning the review, overseeing the database searching and reviewing the written manuscript.

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