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Systematic Review

Methodological Aspects in Study of Fat Stigma in Social Media Contexts: A Systematic Literature Review

Vajisha Udayangi Wanniarachchi *, Anuradha Mathrani *, Teo Susnjak and Chris Scogings

School of Mathematical and Computational Sciences, Massey University, Auckland 0632, New Zealand; t.susnjak@massey.ac.nz (T.S.); c.scogings@massey.ac.nz (C.S.)
* Correspondence: v.u.wanniarachchi@massey.ac.nz (V.U.W.); a.s.mathrani@massey.ac.nz (A.M.)

Abstract: With increased obesity rates worldwide and the rising popularity in social media usage, we have witnessed a growth in hate speech towards fat/obese people. The severity of hate content has prompted researchers to study public perceptions that give rise to fat stigma from social media discourses. This article presents a systematic literature review of recent literature published in this domain to gauge the current state of research and identify possible research gaps. We have examined existing research (i.e., peer-reviewed articles that were systematically included using the EBSCO discovery service) to study their methodological aspects by reviewing their context, domain, analytical methods, techniques, tools, features and limitations. Our findings reveal that while recent studies have explored fat stigma content in social media, these mostly acquired manual analytical methods regardless of the evolved machine learning, natural language processing and deep learning methods. Although fat stigma in social media has gained enormous attention in current socio-psychological research, there exists a gap between how such research is conducted and what technologies are being applied, which limits in-depth investigations of fat stigma discussions.

Keywords: fat stigma; social media; overweight; obesity; analytical method; limitation

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1. Introduction

During the past decade, the popularity of social media has increased rapidly with currently over 4.20 billion social media users worldwide [1], which has affected the way we communicate and interact with each other across the globe. Social media users can easily express their opinions, sentiments and emotions on various emergent topics; however, sometimes such freedom in expressions can result in negatively targeting certain individuals/communities who may be at the receiving end [2]. This could in turn promote discriminatory attitudes towards them. Overtones of sarcasm in online conversations may change overall perceptions, especially when large groups of users post similarly aligned negatively biased comments. Such negative dispositions can give rise to hate speech segments (visual and textual) that can further lead to stigmatization towards certain vulnerable members of society. One of the reasons for sharing negatively charged expressions is anonymity. Anonymity takes away the fear of being identified among users as they write aggressive posts. Without fear of being judged when discussing controversial topics online, such behaviors can cause 'deindividuation and disinhibition' as users freely post negatively laced content in online forums [3] (p. 74). It has been found that users often experience more verbal attacks in online spaces compared to physical spaces. Facebook's algorithms too are fine-tuned around provocative content with reaction emojis being used as "engagement baits" since "clicking the angry reaction is five times more likely to reach a wider audience than a simple like" [4]. Technological advances can therefore have both positive and negative social consequences. Further research is needed to "study strategically about the forces of disruption and innovation shaping the internet civilization" for overcoming such digital nuisances [5] (p. 2).

The worldwide obesity rate has tripled since 1975; and it has been reported that in the year 2020, more than 2 billion adults have been classified as overweight of which 600 million are further classified as obese [6]. This data indicates obesity to be an ongoing problem. As such, social media discussions on obesity and associated topics are rampant and have caused much stigmatization of fat people. Fat stigma, or the social devaluation and denigration towards individuals considered to carry excessive weight [7], has been gathering momentum, which is reflected as hate speech targeting fat people. The connection between obesity and metabolic disorders [8] has fueled stigma discussions that have been further promoted by images of 'ideal' body shapes and sizes by mass media. Body image is described as cognitions, perceptions and attitudes towards one's appearance, which is reflected in how one ranks their bodily features within some measure of overall attractiveness level [9]. Therefore, when thinness is promoted by mass media as the ideal body size and shape, negative attitudes often prevail against people who do not fit within the thin classification. Studies have revealed the biological, psychological and sociological correlates associated with fat stigma studies in social media [10]; however, more studies are needed to decipher the technical details of how these correlates were discovered. Various text mining and machine learning methods including sentiment analysis, topic modeling, emotion analysis and co-occurrence analysis have been implemented in hate speech detection and classification studies e.g., [11–13], etc. These technical methods promote the investigation of large amounts of textual data which assist in unravelling the stigmatizing information that is embedded in the social media discussions. As social media discourses on obesity evolve, examining the methodological approaches used for analysing obesity content in prior literature has enabled us gauge the current state of research in this field of study. Accordingly, the primary research question posed in this study is:
What are the trends in the application of technical and methodological approaches for detecting fat stigma in social media settings?

A review of methods used in prior research studies for identifying fat stigma content expressed over social media has been conducted to answer this research question. Following a systematic literature review approach, we provide an overview of fat stigma studies that have been published in the last decade. The review considers both technical and methodological aspects, such as those related to the study's purpose or concept, data sources used, dataset characteristics (e.g., format and sample size), application of analytical methods, techniques and tools/models, features examined and overall limitations of these studies.

2. Methods

Prior research studies covering fat stigma content in obesity-related discourses over social media have been identified in this work and reviewed by following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol [14]. PRISMA has provided researchers, methodologists, clinicians, medical editors and analysts with guidelines to enable them audit previous research studies and reach an unbiased and rational view of the subject at hand. The PRISMA protocol helps "improve the transparency and the scientific merit" [15] (p. 1) of research progression that is representative of a wider trend. This is further evidenced by the number of systematic reviews that have been conducted on various research topics including that of obesity (e.g., [10,16–18]). It facilitates integrating key elements of relevant research articles by undertaking an iterative process that involves identifying, screening, checking eligibility and then critically appraising each article. A meta-analysis of the inclusion and exclusion criteria is performed to ensure that a proper publication-bias elimination process is followed during selection of the research articles. That is, a full electronic screening process is proposed for examining and scoping articles that need to be considered by specifying search limits (e.g., keywords, abstract, publication date, article library catalogs). Articles that meet the search criteria are confirmed as valid and relevant items for further review.

Our literature review used the EBSCO Discovery Service (EDS) [19]. EDS is a web-enabled resource that integrates search capabilities to filter relevant articles from a wide range of electronic databases (i.e., library catalogs and local digital collections). Search results are presented in a relevancy ranked list that can be further refined by a variety of options (e.g., journal article, book, newspaper). These results are linked to content provider platforms that enable ease of access by further prompting users with links that could take them to full-text content [20].

Using the search words (shown in Table 1) that have been endorsed by Wanniarachchi, et al. [10] we obtained relevant research articles from EDS for this review. Further, we limited the article search to peer-reviewed articles that were published in the English language between 1 January 2012 and 1 January 2022. The search results comprised original quantitative and qualitative research studies that had examined fat stigma in any form and on any social media platform. Each search result's title and abstract were thoroughly examined to extract those articles that were relevant to the study's context, that is, they specifically dealt with fat stigma detection in social media settings. The articles that met the inclusion criteria have next been evaluated to seek out their research design and methods, that is, we sought out the study's purpose or concept, the data sources that were used, the analysis methods that were applied, which techniques were employed and how different tools/models aided their investigation. We also sought to understand the features that were probed during the study's analysis along with the limitations identified by the study.

Table 1. Search Terms.

Context	Search Terms
Fat Stigma	"weight stigma", "obesity stigma", "weight bias", "fat bias", "fat shaming", "body shaming", "obesity", "overweight", "over weight"
Social Media/Online Media	"social media", "social networks", "twitter", "facebook", "youtube", "reddit", "social networking", "online forums", "online media"

Figure 1 describes the four steps—Identification, Screening, Eligibility and Inclusion—used in following the PRISMA protocol for this study. The initial EDS search resulted in 2070 articles. After eliminating 132 duplicates, a rough screening of the titles and the abstracts resulted in further removal of 1861 articles that were further assessed. Next, those wherein the research studies were not based on social media data (n = 55) were excluded from further review. Finally, 22 articles were found to meet our inclusion criteria.

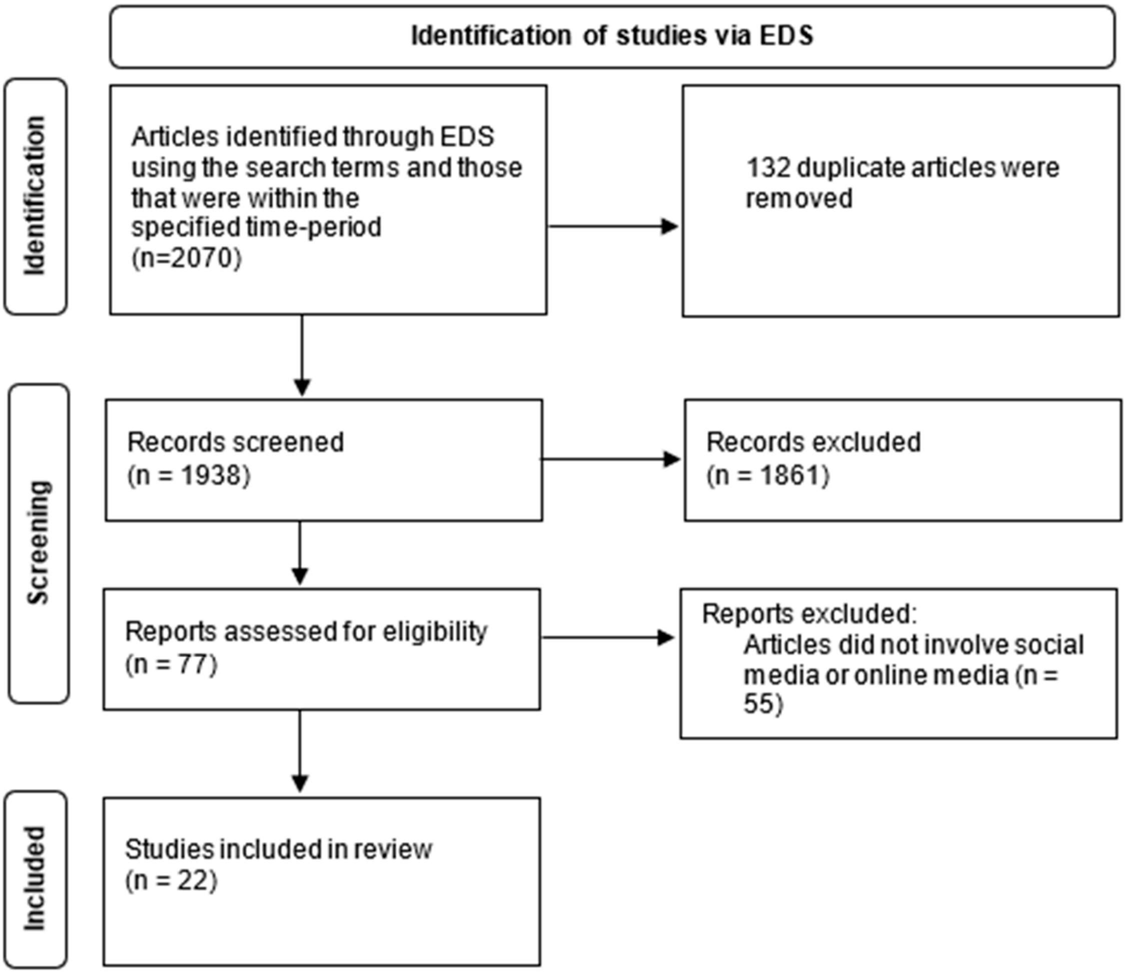

Figure 1. Literature search process (adapted from Page, et al. [14]).

The 22 selected articles have been assessed for the purposes of exploring how experimental activities were conducted, what was the nature of the empirical datasets that were used and which social media platforms were considered. Accordingly, we have structured our review into eight discrete sub-sections: concept (or classification of the problem), domain (which refers to the social media platform being studied), dataset characteristics (or data elements that relate to datatype, participant or sample size), analytical methods (used for interpreting the data), techniques (or procedures employed for examining the data), tools/models (which assisted the investigation), features (used in analyzing the problem domain) and study limitations. Table 2 provides a summary of the technical details that emerged from our review of these 22 articles.

Table 2. Literature on fat stigma in social media.

Citation	Concept	Domain	Dataset Characteristics	Analytical Methods	Techniques	Tools/Models	Features	Limitations
(Yoo and Kim 2012) [21]	Perceptions towards fat people (Examine how obesity is framed and how fat people are portrayed in social media)	YouTube	Videos; 417 videos	Qualitative – Content analysis	Manual coding	N/A	– Themes – Frames	– Actual effect on viewer's perception not tested – No adequate differentiation of audience size, source credibility and potential audience involvement
(Lee, et al., 2013) [22]	Effect of obesity discussions on fat people (Examine the effects of fat-talk in social media)	Facebook	Structured text; 159 American and 137 Korean women participants	Experimental	Regression analysis (statistical analysis)	N/A	Effects of obesity discussions	– Participant's perception of discouraging messages not tested – Effect of the mock-up profile may cause bias – Limited age-range was tested
(Chou, et al., 2014) [23]	Perceptions towards fat people (Examine obesity-related content)	– Twitter – Facebook – Blogposts – Forums – Website comments	Unstructured text; 1.37 million posts	Mixed method – NLP – Qualitative linguistic analysis	– Discourse analysis – Sentiment analysis – Descriptive statistics	N/A	– Sentiments – Themes	– Lack of in-depth analysis in particular areas – No social media channel comparisons – Lack of posters' information – Not analyzing social media conversations
(De Brún, et al., 2014) [3]	Perceptions towards fat people (Examine themes relating to obesity-related discussions)	YouTube	Unstructured text; 2872 comments	Qualitiative – Thematic analysis	Manual coding	Nvivo	Themes	– Difficulty in drawing conclusions regarding informants
(Harris, et al., 2014) [24]	Childhood/adolescents obesity (Examine communication on childhood obesity)	Twitter	Unstructured text; 1110 tweets	Qualitative – Content analysis – Network modeling	– Descriptive statistics – Visualization – ERGM	– IBM SPSS – Pajek 64 – R statnet	– Themes – Network characteristics	– Limitations of using hashtags for data collection

Table 2. *Cont.*

Citation	Concept	Domain	Dataset Characteristics	Analytical Methods	Techniques	Tools/Models	Features	Limitations
(Taniguchi and Lee 2015) [25]	Link between obesity and health issues (Examine impressions of others' self-esteem, psychological well-being and physical attractiveness)	Facebook	Structured text; 159 American and 102 Japanese women participants	Experimental	Statistical analysis	N/A	Characteristics of obesity-related discussions	– Did not conduct a manipulation check – Possibility of taking posts as white lies not tested – BMI of profile owner is unknown
(Kent, et al., 2016) [26]	Link between obesity and health issues (Examine how obesity and cancer discussed together)	– Twitter – Facebook	Unstructured text; 1382 posts	Mixed methods – Quantitative approach embedded descriptive qualitative analysis	– Manual coding – Sentiment analysis – Bivariate frequency analysis	SAS	– Themes – Sentiments	– Lack of sociodemographic data – Temporal effects on comments – Lack of knowledge on commenters' characteristics
(Lydecker, et al., 2016) [27]	Perceptions towards fat people (Examine weight stigma)	Twitter	Unstructured text; 4596 tweets	Qualitative – Content analysis	Manual coding	N/A	– Themes – Sentiments	– Inherent privacy constraints for Twitter – Limited data sample – Search keyword is limited to 'fat' – Subjective nature of coding process
(So, et al., 2016) [28]	Perceptions towards fat people (Examine prevalent beliefs and attitudes about obesity)	Twitter	Unstructured text; 120 tweets	Qualitative – Content analysis	Manual coding	N/A	– Themes – Emotions – Causes	– Not ascertaining the resulting emotions – Not identified the network aspect of the messages
(Webb, et al., 2017) [29]	Link between obesity and health issues (Examine strategies used to represent and motivate fat-accepting lifestyle)	Instagram	Images; 400 images	Qualitative – Content analysis	Manual Coding	IBM SPSS	Themes	– Temporal effects on the results

Table 2. *Cont.*

Citation	Concept	Domain	Dataset Characteristics	Analytical Methods	Techniques	Tools/Models	Features	Limitations
(Brooker, et al., 2018) [30]	Perceptions towards fat people (Examine connection between linguistics and computer-mediated form regards to fat stigma)	The Guardian online	Unstructured text; 1452 comments	Qualitative – Frame analysis	Co-occurrence analysis	Textometrica	Themes	Limited ability to navigate through comments corpus
(Holmberg, et al., 2018) [31]	Link between obesity and health issues (Examine the implications regarding the use of social media in clinical settings)	N/A (Data not directly acquired from social media)	Structured text; 20 participants	Qualitative – Interviews with participants using multiple social media platforms	Manual coding	N/A	Effects of fat stigma	Not reflected the experience of obese adolescents in general population
(Jeon, et al., 2018) [32]	Perceptions towards fat people (Examine anonymous verbal attacks)	YouTube	Unstructured text; 316 comments from 2 videos	Qualitative – Content analysis	Manual coding	N/A	Characteristics of obesity-related discussions	– Study is exploratory – Sampled only root comments – Not identified the response of fat people to verbal attacks
(Karami, et al., 2018) [33]	Link between obesity and health issues (Examine public opinion on diabetes, diet, exercise and obesity)	Twitter	Unstructured text; 4.5 million tweets	Qualitative – Content analysis – Topic modeling	– LDA – Lexicon based approach	LIWC	– Themes	– Not considered geographical location – Limited number of queries – Time period of data collection – Not tracked individuals' tweet changes
(Lim and An 2018) [34]	Childhood/adolescents obesity (Examine the effect of body image content on obesity stigma)	N/A (Data nt directly acquired from social media)	Structured text; 202 participants	Quantitative – Survey questions given to adolescents who use social media	Regression analysis (statistical analysis)	N/A	Effects of obesity discussions	N/A

Table 2. *Cont.*

Citation	Concept	Domain	Dataset Characteristics	Analytical Methods	Techniques	Tools/Models	Features	Limitations
(Yeruva, et al., 2019) [35]	Link between obesity and health issues (Examine the relationship between obesity and healthy eating)	– Twitter – PubMed	Unstructured text; 103609 Twitter and 6602 PubMed article abstracts	Qualitative – Content analysis – NLP – Topic modeling	– TF-IDF – Word embeddings – Sentiment analysis – Co-occurrence analysis – LDA – Word2Vec	– Apache spark – Tensor Flow – CoreNLP – VADER – TextBlob	– Sentiments – Co-occurrences – Themes	– Basic NLP techniques are not fully explored in finding contextual word embeddings – Framework is not thoroughly evaluated – Limitations on result interpretation
(Mitei and Ghanem 2020) [36]	Perceptions towards fat people (Examine obesity discussions)	Twitter	Unstructured text; 2500 tweets	Quantitative – Cluster analysis – User analysis	Social media clustering	– Clauset-Newman-Moore clustering algorithm – NodeXL	Characteristics of obesity-related discussions	– Size of the dataset – Time period for data collection – Limited adaptation of machine learning techniques
(Busam and Solomon-Moore 2021) [37]	Childhood/adolescents obesity (Examine how childhood obesity has framed)	Facebook	Unstructured text; 11 newspaper outlets, 30 news articles and 1104 responding comments	Qualitative – Frame analysis	Manual coding	– R studio – Nvivo	– Frames – Themes	– Automated restructuring of articles and comments in Facebook – No demographic data – Could not tackle headline framing
(Chansiri and Wongphoth-iphan2021) [38]	Effect of obesity discussions on fat people (Examine the effect of idealized social media images)	Instagram	Structured text; 221 female participants	Experimental	MMMA	N/A	Effects of idealized images	– Uncertainty regarding casual effects from mediator to dependent variable – No firm conclusion regarding idealized social media images – Small sample size
(Lazarus, et al., 2021) [39]	Link between obesity and health issues (Examine stigma for NAFLD/NASH and obesity)	Twitter	Unstructured text; 18 274 NAFLD, 2621 NASH and 10 million tweets	Qualitative – Content analysis	– Sentiment analysis – Discourse analysis	– Self-developed NLP module – Dataturks platforms	– Sentiments – Themes	– Impact of temporal trends – Bias in labelling tweets – Limited obesity discourse in NAFLD/NASH dataset – Limitations in data annotation

Table 2. *Cont.*

Citation	Concept	Domain	Dataset Characteristics	Analytical Methods	Techniques	Tools/Models	Features	Limitations
(Lessard and Puhl 2021) [40]	Childhood/adolescents obesity (Examine perceived changes in weight stigma from peers, parents and social media during the pandemic)	N/A (Data not directly acquired from social media)	Structured text; 452 participants	Quantitative – Survey questions were given to adolescents who use social media	Statistical analysis	IBM SPSS	Characteristics of obesity-related discussions	– Data were largely descriptive – Not carried out pre-pandemic studies – Self-reported and single-item assessments are not validated – Sample focused on U.S. adolescents only
(Bograd, et al., 2022) [41]	Perceptions towards fat people (Classify sentiments towards fat acceptance movement)	Twitter	Unstructured text; 2000 tweets	Qualitative – Content analysis	– Sentiment analysis – Manual coding	– AWD-LSTM – ULMFiT	– Sentiments – Supportiveness for Fat Acceptance Movement	– Limited annotators and dataset – Results subject to minor variations on model precision and recall – Twitter users cannot be taken as a proxy for the general public

3. Findings

This section consolidates findings from our exploration of the selected 22 research articles. Before we expand on the methodological and technological findings, we have grouped these articles based on their year of publication to highlight the growing interest in investigating fat stigma content expressed over social media. Figure 2 illustrates an ongoing interest in this topic throughout the last decade with a noticeable rise of interest shown in 2018 and 2021. This trend is continuing with a publication on this topic in the first month of 2022 (which was the closing time of this review). Further evidence on the nature of the research designs that were applied in these selected articles is summarized in Table 2 and are presented in the order of their year of publication.

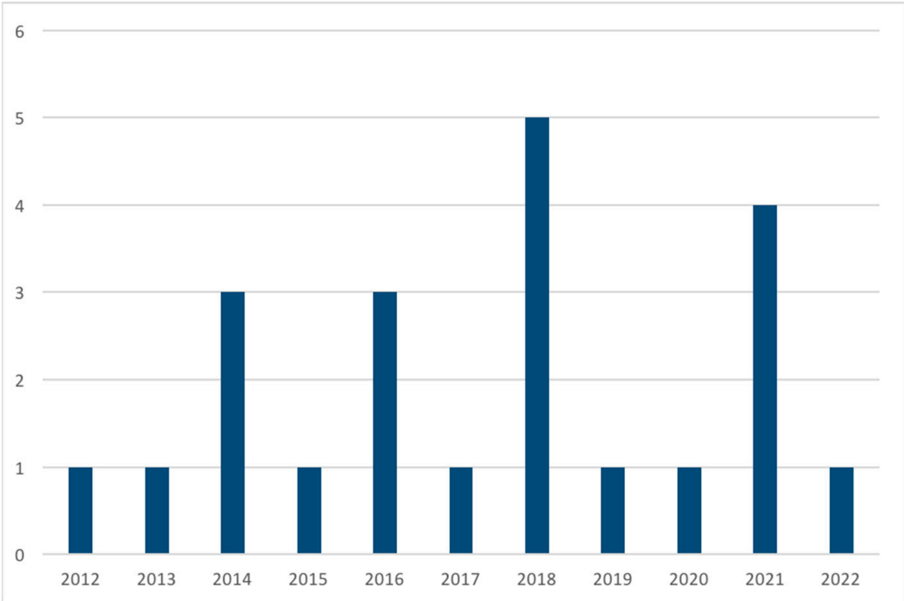

Figure 2. Number of articles by year.

We have divided our findings into eight subsections, namely, concept, domain, dataset characteristics, analytical methods, techniques, tools/models, features and study limitations. These subsections highlight the trends that emerged from the selected articles on those topics. Each of these is described next.

3.1. Concept

Each article has been examined in order to draw out the dominant concept that signified the form of fat stigma being portrayed. Most of these studies aimed at identifying how users project their views in obesity-related discussions over social media forms to enable understanding of their perceptions towards fat people [3,21,23,27,28,30,32,36,41]. A few other research studies focused on the effect of obesity-related discussions on fat people and their usage in clinical settings [22,38]. When studying the implications of fat stigma content in social media, the effect that idealized body images have on fat people and on their close contacts, peers and parents are also taken into consideration.

Other concepts that have been categorized are based on childhood/adolescents' obesity [24,34,37,40] and the link between obesity and associated health issues [25,26,29,31,33,35,39], with one other study's focus on mental health issues [25]. Only two articles conducted gender specific research, that is, these studies employed female participants to investigate the effects of obesity-related discussions on them [22,25].

3.2. Domain

The domain refers to the social media platform that provided the researchers with the empirical dataset for their investigation. Ten of the review articles used Twitter as the data source [23,24,26–28,33,35,36,39,41], while nine considered other social media platforms, such as YouTube, Instagram, Facebook and public websites (e.g., newspaper comments) [3,21,22,25,29,30,32,37,38]. Three articles did not acquire data from social media platforms, rather, they surveyed and interviewed social media users [31,34,40]. Almost all the articles that used empirical data extracts from social media domains considered only one social media platform for retrieving data, although two articles gathered data from two or more social media platforms [23,26]. We did not find evidence of data extracts from the Reddit platform, an upcoming social media platform, that has rich textual content [42] which is organized into user-created communities referred as 'subreddits'. Figure 3 illustrates a breakdown of the domains used in the selected literatures for extracting/collecting empirical data in their investigation of fat stigma content.

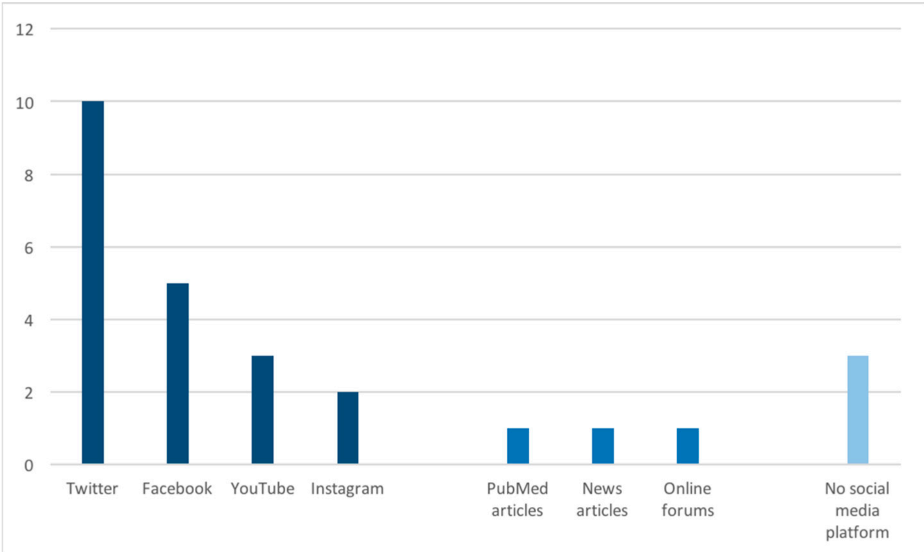

Figure 3. Domains used for data collection in selected literature: Social media domains (darkest blue), other online domains (blue) and online media not used (light blue).

3.3. Data Characteristics

As a variety of data sources were used, the characteristics of the datasets thus collected have exhibited considerable differences in both the size of the data samples and in their format (i.e., structured/unstructured text, images, videos). Only four articles indicated a sizeable data collection, that is, these studies have extracted more than 10,000 data records (i.e., posts, tweets, etc.) from social media platforms and among these, three articles had collected obesity-related data records in the order of millions [23,33,39]. Two articles closely analyzed videos on YouTube to explore how fat people are portrayed in visual displays [21,32]; further, one other article used images to analyze the effect of body ideals on fat individuals [29]. Finally, several other research articles examined the effect of obesity-related discussions and experiences of being exposed to stigmatizing content by interviewing and monitoring human participants [22,25,31,34,38,40]. This variation in data characteristics across the 22 articles being reviewed calls for different analytical methods, diverse techniques and a wide array of tools/models for conducting subsequent analysis.

3.4. Analytical Methods

The articles under consideration used different analytical methods for investigating obesity-related extracts from social media, with most of them having used qualitative methods. Only three articles employed quantitative methods [34,36,40], while another three carried out experimental work [22,25,38] and two other articles used mixed methods by incorporating both quantitative and qualitative research methods [23,26].

Most of the qualitative research that was undertaken has indicated researchers' interest in employing content analysis that includes video analysis, textual analysis and visual content analysis. Apart from content analysis, two articles have considered frame analysis [30,37], two applied topic modeling methods [33,35] while another two employed natural language processing (or NLP) methods [23,35]. The distribution of analytical methods used are illustrated in Figure 4, where we grouped them as qualitative, quantitative, experimental and mixed methods.

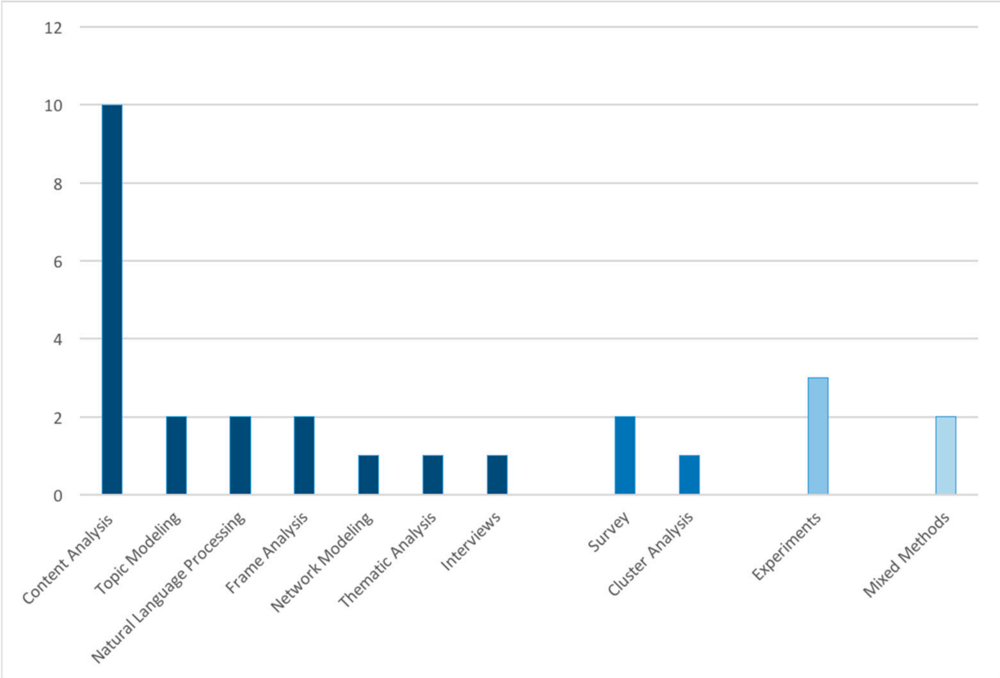

Figure 4. Analytical methods used: Qualitative (darkest blue), quantitative (blue), experimental (light blue) and mixed methods (lightest blue).

3.5. Techniques

Among the techniques incorporated for the data analysis, it is highly noticeable that most of these articles were investigated by using manual coding techniques to carry out their content analysis. Sentiment analysis too has been employed by five research articles [23,26,35,39,41] where LDA and Mallet implementation of LDA were used to perform topic modeling by Yeruva, et al. [35] and Karami, et al. [33] respectively. Statistical analysis has been conducted by four articles [22,25,34,40] of which two considered regression analysis techniques. Although discourse analysis and co-occurrence analysis have been widely discussed techniques for hate speech detection, we find that only two studies have applied discourse analysis while another two applied word co-occurrence analysis amongst the selected literature.

Apart from these commonly used techniques, some studies employed specific techniques to analyze social media data. Harris, et al. [24] used ERGM (exponential random graph modeling) which is a widely used technique to analyze social network structures. ERGM assisted them in estimating the probability of a tie between any 2 Twitter users based on their characteristics and network structure. TF-IDF (term frequency inverse document frequency) and word embedding were among the few analytical techniques used by Yeruva, et al. [35]. Using TF-IDF, the study collected data from two social media domains that were then used in word embeddings to extract the context of words used in these collected datasets. Social media clustering has been used by Mitei and Ghanem [36] to analyze relationships such as friends, followers, etc., to acquire details of obesity-related social network characteristics. Kent, et al. [26] have used bivariate frequency analysis, along with sentiment analysis and manual coding techniques, to statistically analyze the number of occurrences of obesity and cancer in social media platforms. The application of MMMA (moderated moderated mediation analysis) to explore complex media effects by enabling multiple individual differences was studied by Chansiri and Wongphothiphan [38]. The authors applied MMMA with appearance comparisons as the mediator and further with BMI and perceived weight as the moderators to identify the effects of fitspiration and thinspiration on women's self-esteem.

3.6. Tools/Models

While a majority of these articles have conducted manual coding to analyze the visual and textual contents, it is interesting to note that most of these studies have not used any type of software tool (or algorithm) to assist their analysis. Popular tools that have been prescribed for content analysis in hate speech detection to reduce datasets by classifying them into relevant categories (that are specific to the topic under investigation) is not evident in their usage in selected literature. Rather, we find much use of statistical analysis with IBM SPSS [43] in many research investigations [24,29,34,40] in comparison to R [44] and SAS [45] which have recently emerged as strongholds of statistical measures. In having said this, we also witnessed a collective usage of several emergent modelling tools in five studies [24,35,37,39,41]. For instance, Lazarus, et al. [39] developed a NLP (natural language processing) model to analyze the sentiments of the data corpus and used DataTurks platform for manual data annotation. LIWC (Linguistic Inquiry of Word Count) is used by Karami, et al. [33] to identify health related topics as it assisted in revealing thoughts, feelings, personality and motivations within a given corpus. Yeruva, et al. [35] used Apache Spark and TensorFlow to implement their proposed framework. They further employed VADER (Valence Aware Dictionary and sEntiment Reasoner), CoreNLP and TextBlob for obtaining more accurate sentiment analysis in the corpus. The application of Textometrica on word co-occurrence analysis has been studied by [30]. NodeXL was used by Mitei and Ghanem [36] to construct social network graph for the dataset and further examine the clusters formed as a result of retweets, replies and mentions using Clauset-Newman-Moore clustering algorithm. After experimenting with different machine learning algorithms, Bograd, et al. [41] have used ULMFiT (Universal Language Model Fine-Tuning), a recurrent neural network-based model, to acquire better contextualized representations of words in a corpus. ULMFiT employs a language model (LSTM: long short-term memory) for processing sequential sequences using iteratively averaged weights (referred as weight-drop) to efficiently analyze large volumes of textual data (e.g., AWD-LSTM). Thus, NLP tools are gathering attention by researchers to enable them to delve into a variety of optimization strategies for language modelling and sequence learning tasks.

3.7. Features

Next, we examined the features of obesity-related discussions prevalent in the selected literature: that is, we inspected which aspects of fat stigma have been tackled by recent research studies. It was evident that most of these studies focused on identifying key themes (e.g., lifestyle, behavior, attractiveness, diet, etc.) associated with fat stigma or obesity-related contents in social media. However, several studies investigated the underlying fat sentiments that are spread via obesity discussions [23,26,27,35,39,41], with one study having tracked which emotions are mainly expressed within such discussions and the causes of fat stigma [28]. Other characteristics of obesity-related discussions including perceptions, gender, user, network, etc., have been explored by five studies [24,25,32,36,40]. Determining the effects of fat stigma or obesity-related content seems popular among researchers as four studies have been conducted to unravel aspects of social media interactions and roles that impact vulnerable members of society who are on the receiving end [22,31,34,38]. Chansiri and Wongphothiphan [38] studied the effects of idealized body images on fat people while the rest of the studies reviewed the effects of obesity-related discussions. Two studies framed the obesity content in social media into behavioral, societal, medical or healthy eating frames [21,37]. One study focused on identifying the supportiveness received by fat people from social media [41] while another revealed more details of word co-occurrences that exist in obesity discourses. Figure 5 illustrates prevalent features of obesity content as was discovered from these research studies.

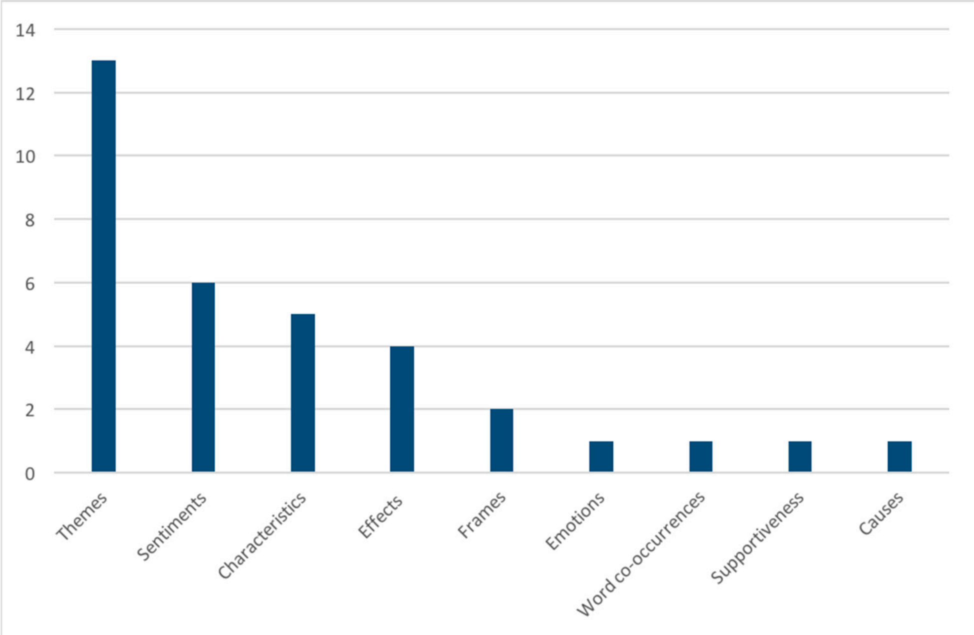

Figure 5. Features investigated by selected literature.

3.8. Limitations

The most common limitations observed from our review were associated with size of the empirical dataset used for analysis [27,33,36,39,41] and the annotation process which comprised few annotators [39,41]. Some studies have considered the subjective nature of their manual coding and annotation process as a limitation [27,39] while few other studies suggest that if the occurrence of events are not captured timely, then temporal trends cannot be captured [26,29,39]. Apart from these common limitations, more specific limitations were identified by each of the articles relating to the nature of their study (e.g., data screening, bias in tagging of tweets, lack of validation by experts). Finally, data collection, in particular, the collection of user data (e.g., geographical data, sociodemographic data, user characteristics) was voiced as being difficult to capture due to privacy constraints of social media platforms.

4. Discussion

This study demonstrates the many technical and methodological aspects in the analysis of obesity content extracted from social media posts for gaining insight on fat ideologies. Using a methodical strategy, we filtered 22 research articles that were thoroughly examined in order to examine gaps between technology use and sociopsychology research. Though most of the selected articles were published between 2018 and 2021, we found relevant articles in years leading up to this period, which highlights a growing research interest in understanding fat stigma trends.

The findings of this review highlight how fat stigma studies have been conducted in recent years. It has identified elements of data acquisition, analytical methods, tools that have been incorporated and techniques utilized alongside the key features studied in each of the selected fat stigma research. These findings have aided in discovering trends showcasing common technical and methodological designs used and have thereby revealed possible gaps that need attention in future obesity research. Moreover, we have presented a snapshot of limitations (as expressed by the authors of these articles) in interpreting and providing more substantive results. Therefore, our comprehensive analysis provides directions for the conduct of future research on the application of upcoming design methods in the study of data extracts from social media.

Our review finds that research studies have mainly investigated how fat people are positioned in obesity content rather than analyzing the effects of such content on fat people. One of the reasons for such a tendency would be the ethical dilemma that researchers are faced with when closely studying the effect of negative content on human participants [46]. Closely monitoring fat person's feelings when exposed to negative obesity-related content in social media can indirectly affect these individuals who are participating in the study; therefore, a cautious approach towards maintaining ethical and social boundaries in the pursuit of this type of research is advocated. Such caution, on the contrary, is not an issue while studying publicly available discourses; rather, these discourses are enriched with obesity content and can be more easily examined to understand how fat people are being portrayed. Researchers are provided with more freedom to pursue in-depth analysis of sensitive topics to a larger extent.

The effect of close contacts such as peers and parents has been studied only once in the recent decade. However, more research on the effect of stigmatizing behavior of close contacts such as friends and relatives need to be studied, since the effect of such behaviors can greatly impact an individual in comparison to remarks made by any random stranger. Although social media is often considered as a platform where users are being exposed to a larger audience, it is also a representation of the society we live in since users are subjected to a breadth of ideas, opinions and sentiments from friends and relatives. As a result, there is a higher possibility of being stigmatized by a close relation than by a stranger. Having awareness of such online experiences can help us understand the effect of fat stigma on a fat individual by their friends or relatives.

Many studies have monitored the association between obesity and health issues based on the nature of the obesity content. This can be considered as a positive trend; with obesity having been recognized as an epidemic by WHO [6], these online discussions that revolve around health and obesity can further our understanding of public perceptions. It can help us better interpret the association between them and discern societal fears and apprehensions towards obesity to help remove uninformed myths that surround obesity-related health issues. We found that only two studies investigated the effects of obesity-related discussions on females. Unravelling fat stigma discussions can help us gain insights on female body objectifying content [47] to assist in raising awareness of the impact of such objectification in society.

The domains used by selected research studies were observed. Twitter is visibly the most popular social media platform among researchers and the reason could be that Twitter facilitates easy data collection and showcases quick user responses to latest world events [42]. However, Reddit now facilitates the same criteria, besides, it offers more extensive textual content compared to the limited character of tweets. Reddit has become one of the most prominent social media platforms with 52 million active users [48], therefore, it should also be considered as a useful fact-finding setting for conducting fat stigma research. Further, the rapid growth of social media popularity means that most individuals are likely to be active on more than one social media platform. In addition, the data types, data lengths, or data formats are different in each social media platform. Therefore, social media studies need to expand to multiple platforms; this will establish better comparisons and contrasts on obesity-related content.

Although millions of social media posts/comments are shared daily, only three studies have collected more than 10,000 comments/posts in selected literature. The main reason behind this could be the limitations of many social media APIs when retrieving data. For example, Twitter allows retrieval of past data for only up to 7 days only [49]. This limits the number of data that can be retrieved at one time. Therefore, to obtain a larger dataset, the data needs to be collected daily for a considerable amount of time and this may pose time and resource limitations. Further, most of the datasets used in literature have consisted of textual datasets, with very few articles having analyzed videos and images. This may be due to the rapid developments in textual data analysis methods compared to visual data analysis. However, as fat people can also be stigmatized visually [50], more research on visual obesity-related content analysis is needed.

Majority of the articles indicated content analysis as their main analytical method; this can be attributed to them having collected textual data for their analysis. Analysis of textual social media data to detect hate speech has been a popular research topic in the recent past and many research studies have employed machine learning [51–53] and deep learning [54–57] methods to achieve hate speech detection. However, instead of using technical methods, many articles that studied fat stigma in social media have adopted manual coding methods, which is subjective to the perspectives of research teams. One reason for not employing machine learning or deep learning methods would be that these methods mostly consider single type textual features [12]. Therefore, by using machine learning and deep learning methods, the researcher either has to neglect other rich textual information or combine different methods to attain improved fat stigma detection. Chen, et al. [58] reason that people who are trained in qualitative methods are generally not trained in machine learning techniques. Moreover, social scientists frame their research around deduction, causality or hypotheses, unlike computational scientists who depend upon experiments wherein the data is frequently independent of any assumptions. While the precise reasons behind the use of manual coding in favor of technical approaches within our selected papers is unclear, the limitation in technology adoption in obesity research is evident. The growth of different machine learning tools and algorithms does not appear to have significantly influenced fat stigma research methodologies. As a result, many of the selected papers in this study did not use any software tool or algorithm for their analysis. We find that majority of studies have used statistical analysis tools such as IBM SPSS. Therefore, it can be concluded that a clear gap exists between obesity research methodologies and technology use; hence, more practical content analysis frameworks are required. We acknowledge that using a different academic database or using different search terms could yield another viewpoint. However, we followed a systematic approach for selecting the 22 research articles to eliminate any publication bias in our selection process.

The limitations of methods applied in the selected articles provide grounds for future research directions and informs on what technical details require closer attention in future studies. Many studies considered limited data quantities in their evaluation of fat stigma themes. As most of these studies considered manual coding, the amount of data that could be manually coded or annotated is understandably limited. This may be the main reason behind the small data samples in the reviewed articles. Further, a biased or subjective coding process due to manual coding has been considered a limitation by few studies and some have even highlighted the limited number of annotators used in the process. These limitations are linked with the adaptation of manual coding techniques for processing and analyzing the data. Therefore, the adaptation of existing text mining, machine learning and deep learning techniques could be further justified, since these would minimize the limitations observed in this review. The temporal effect of trends on social media conversations is considered a limitation by few studies. Certain global events, such as pandemic situations, war, etc., could impact what people discuss on social media and also change the perception of certain topics such as obesity. Although one study has analyzed the perception of obesity during the COVID-19 pandemic [40], more such studies could detect trends of how perceptions deviate based on different current events. Some studies have emphasized the inability to acquire different types of textual information such as geographical location, demographical information and BMI of users and different conversational methods such as replies, retweets, etc. These limitations mainly occur due to privacy constraints imposed by social media platforms to secure users' anonymity. However, the revelation of this information could benefit in developing hate speech detection strategies in future.

5. Conclusions

This paper has examined the literature that studied fat stigma or obesity-related content in social media in the past decade. A systematic literature review addressed the technical aspects which have been employed in prior articles (published between 2012 and early 2022) with specific focus on the investigation of fat stigma or obesity-related social media discussions. Of the 22 research articles that informed our literature review, we identified eight technical categories. These are concept, domain, data characteristics, analytical methods, techniques, tools/models, features and study limitations. The findings within each of these categories have been consolidated to provide a coherent view on currently used methodological approaches for the study of fat stigma and suggest possible research methods for inspecting fat stigma discussions in social media platforms. Our review highlights recent trends in research approaches (both technical and methodological) that have been used over the past decade for the study of fat stigma and therefore, it has implications on the conduct of future research approaches.

From our review, we have uncovered many limitations in existing fat stigma research. For one, most studies have considered a limited amount of data for their analysis. Social media is one of the key communication methods nowadays; therefore, considerably larger datasets could be acquired. We suggest future research should focus on data expansion using existing social media data acquisition techniques. A reason commonly cited by prior studies for selecting small datasets is the difficulty that large datasets pose in manual coding and analysis. However, content analysis and text mining have been much improved with automated approaches, such as with machine learning, NLP and deep learning. Therefore, future fat stigma research could incorporate these approaches to analyze larger datasets effectively and efficiently. With adaptation of multiple analytical techniques, future research could be significantly enhanced and could help unravel different dimensions or discover deeper meanings associated with fat stigma (or similar other hate speech topics). Secondly, most studies have considered only one social media platform, although social media users tend to use more than one platform to acquire information and share ideas. Future research could be strengthened by gaining perspectives from multiple social media platforms. Finally, we call upon social science and computational researchers to jointly leverage their skills and know-how to overcome these mentioned limitations and further develop the field of social computing. Given the strengths prevalent in both fields, collaborative research can help overcome the limitations that have been identified in this literature review of studies that have been conducted over the last decade.

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