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Using social media in social research: Opportunities for enhancing large-scale surveys

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Contents

Introduction

In the past decade, social media has become “an integral part of everyday life with large economic, political, and societal implications” (1). There are currently 3.48 billion active social media users worldwide, equating to 45% of the global population (2). This number has increased by 280 million during the previous year and the trend is likely to continue (3), with networks such as Facebook and Twitter reporting year over year increases[1]. As more people engage with social media each year, there is an increased opportunity to gather vast amounts of naturally-occurring data on a range of subjects including – but not limited to – consumer behaviour, political views or attitudes towards policies (4).

There are three key approaches to the use of social media in research. First, the novelty of social media allows ‘augmentation’ – i.e. a deeper understanding or fresh perspective - of phenomena already known. Secondly, social media can be used to replace traditional data collection tools such as surveys. Thirdly, social media can be linked to existing datasets (e.g. data obtained from surveys), enabling ‘cross-verification’ or calibration of social phenomena or enhancing existing datasets. Third approach most relevant, examples what the possibilities are This review discusses how these approaches translate into different methodologies.

The aim of this scoping review is to identify research methodologies or tools that could potentially be used to enhance large-scale surveys, and in particular the CLS cohort studies . This review addresses the following research questions:

- How is social media data used in social research?
- What are the opportunities and challenges of using social media data?
- What are the possibilities for enhancing large-scale surveys by linking to social media data?

As this is an emerging field of social science, the scoping study does not intend to be an exhaustive exploration of all available literature. Instead, the review focuses on the empirical use of social media in three areas of social science to illustrate the research potential of social media data and examines the methodological challenges of linking social media data to surveys.

Social media: Definition and types

There are relatively few formal definitions of the term ‘social media’, an umbrella term which covers a growing number of technology platforms with very diverse features designed for different purposes. Social media classifications can be made based on *what processes* they enable (e.g. communication, creation, sharing), *how* these processes occur (e.g. instant or archived content), or what *type of content* is predominant (e.g. text, image, video). The SAGE *Handbook of Social Media Research Methods* (5) describes ten types of social media as below (see Table 3 in Appendix for full description):

[1] In April 2019, Facebook reported the following worldwide figures: 1.56 billion daily active users (DAUs) and 2.38 billion monthly active users (MAUs); both figures had increased by 8% year over year (53). At the same time, Twitter reported 262 million internationally (3% increase year over year), and a 11% year over year increase in DAUs (54)

Table 1.Social media types. Based on (1)

Social media type	Examples
Social networking sites	Facebook, LinkedIn
Bookmarking	Delicious, StumbleUpon
Microblogging	Twitter, Tumblr
Blogs and forums	Wordpress
Media sharing	YouTube, Pinterest
Social news	Reddit
Collaborative authoring	Wikipedia
Web conferencing	Skype
Geo-location based sites	Foursquare, Tinder
Scheduling and meeting	Doodle, Google Calendar, Microsoft Outlook

The Handbook authors also propose a comprehensive definition of social media:

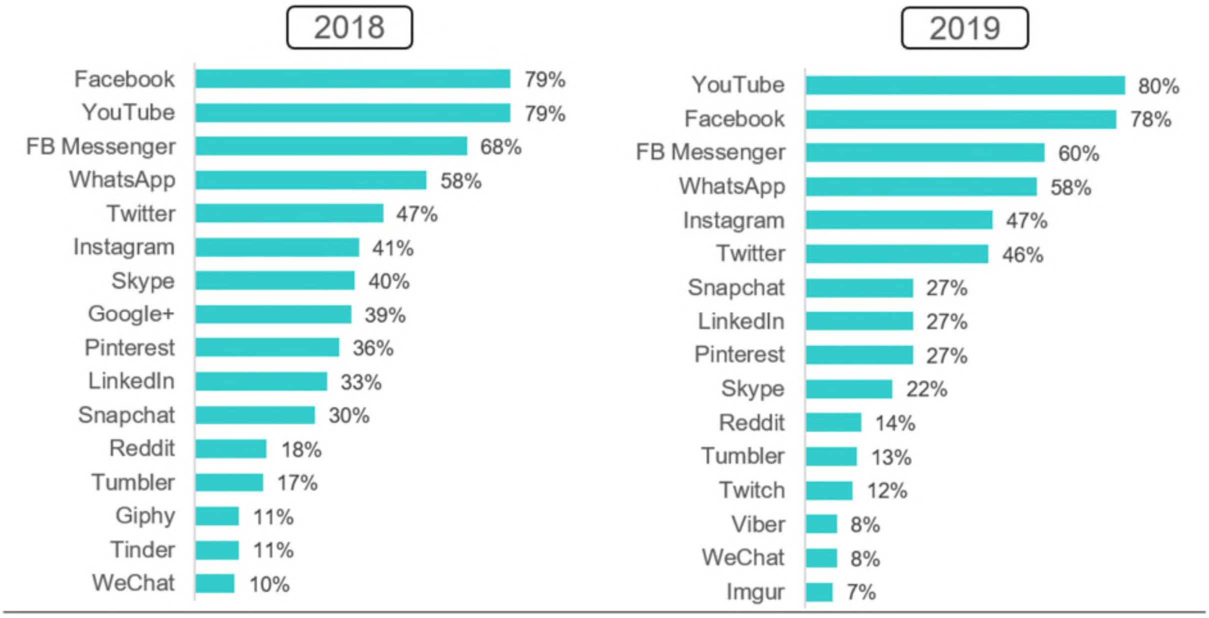
> “Social media are web-based services that allow individuals, communities, and organizations to collaborate, connect, interact, and build a community by enabling them to create, co-create, modify, share, and engage with user-generated content that is easily accessible.” (1)

Social media users in the UK

In the UK, there were 45 million social media users in January 2019, representing 67% of the national population and the majority (39 million) access social media using a mobile device (6). The platforms with the most monthly active users[2] (in millions) include: Facebook (40 m), LinkedIn (27 m), Instagram (24), Snapchat (17.15 m) Twitter (13.60 m) (6). However, when considering user *reported use*, the list now includes YouTube, Facebook Messenger, and WhatsApp as shown in figure 1. While many of the platforms used broadly in the UK in 2019 can be defined as social networking sites, two of the four platforms used by over 50% of UK internet users are in fact multi-purpose messaging apps – Facebook Messenger and WhatsApp – and one, a media sharing site, YouTube. Data obtained from a nationally representative sample of 2,008 adults aged 18 or more (7) found similar rankings in 2018, as shown in the right side of figure 1.

[2] Based on advertising audience statistics published by the companies.

Figure 1. Social media use in the UK. Based on (6) **and** (7) **(survey-based)**[3]



Age related differences between social media use are shown in table 2 (based on (7)). Younger adults tend to embrace 'newer, niche apps' such as WhatsApp, Instagram, Snapchat and Pinterest, while those aged over 65 generally favour Facebook.

Table 2. Social media use in the UK in 2018 by age group. Based on (6) **(survey-based)**

	18-24	25-34	35-44	45-54	55-64	65-75	75+
Most used	YouTube	YouTube	YouTube	YouTube	YouTube	Facebook	Facebook
2	Facebook	Facebook	Facebook	Facebook	Facebook	YouTube	YouTube
3	Facebook Messenger	Facebook Messenger	Facebook Messenger	Facebook Messenger	Facebook Messenger	Facebook Messenger	Facebook Messenger
4	Instagram	WhatsApp	WhatsApp	WhatsApp	WhatsApp	WhatsApp	Skype
5	WhatsApp	Instagram	Twitter	Twitter	Twitter	Skype	WhatsApp
6	Snapchat	Twitter	Instagram	Skype	Skype	Google+	Twitter

Methodology

The review is based on the framework developed by Levac *et al* (8) and recommended by Colquhoun et al (9). The framework is comprised of the following stages: *1. Identifying the research question; 2. Identifying relevant studies; 3. Study selection; 4. Charting the data; 5. Collating, summarising, and reporting the results; 6. Consultation with stakeholders (optional).*

[3] Both (6) and (7) present survey-derived data on social media usage in the UK but it is unclear from the reports how they measured it.

The identification of studies (step 2) used Google search engine searches, a general search using SCOPUS citation and abstract database (the 'base search') using keywords such as 'social media' and 'empirical'. We chose three relevant scientific areas in which social media data could help enhance the social surveys and for which social media has been widely used for research: *mental health, politics and public sphere* and *social capital*, Next, specific searches for 'social media' and the three themes were performed in the specialist journals Social Media + Society, Social Network Analysis and Mining, New Media and Society, Big Data and Society, Journal of Computer-Mediated Communication, and Information, Communication & Society. In addition to this, relevant conference websites were consulted[4]. A discussion with Dr Luke Sloan, a Cardiff University School of Social Sciences researcher with considerable expertise in the field, helped identify relevant references, such as The SAGE Handbook of Social Media Research Methods (5).

Study selection (step 3) was an iterative process which involved repeated readings of article abstracts and methodology chapters. Key inclusion criteria referred to:

- Studies used data derived directly from social media - as opposed to surveys about the use of social media;
- Studies were conducted on adult, resident populations[5] – as opposed to children or teenagers;
- Studies explores one of the three areas of interest: mental health, politics and the public sphere, or social capital.

Data charting (step 4) was used by keeping spreadsheet records of the findings. Collating, summarising, and reporting the results (step 5) focused on extracting the common themes and methodological features of the studies. Stakeholder consultation (step 6) was carried out regularly, i.e. weekly meetings with the project supervisor.

The key challenges of scoping studies are determined by the need to "balance breadth and comprehensiveness…with feasibility of resources" (8). Therefore, while the review primarily focuses on empirical, peer-reviewed literature published in academic journals or conference proceedings, it also includes grey literature and sources recommended by experts in the field or retrieved from dedicated social media research groups.

Findings

Our findings cover two main areas. Firstly, we summarise findings from the social media research literature in our three thematic areas. Secondly, we discuss the methodological issues and challenges of enhancing large-scale surveys by linking to social media data.

Using social media for social research: findings about mental health, politics and social capital

The scoping review includes thirty articles published in peer-reviewed journals or conference proceedings that illustrate some of the empirical uses of social media in social research. We chose three relevant scientific areas in which social media data could potentially help

[4] Association for Computer Machinery (ACM) International Conference Proceeding Series (55) and BigSurv18 (56).
[5] This was important because the CLS studies involve UK born participants generally over the age of 20.

enhance social surveys and for which social media has been widely used for research: mental health, politics and public sphere and social capital. In this section we summarise findings from the social media literature in these areas.

Mental health

Fourteen articles employed social media to empirically identify aspects related to mental health, including six empirical experiments (10–23). Most of these studies introduce empirically-tested models, methods or frameworks of identifying mental health conditions based on social media data (11–16,18–23). In addition to this, three reviews of literature on the use of social media in mental health research were identified (24–26).This section focuses on the fourteen empirical studies and draws insights from the literature reviews.

The fourteen empirical experiments and models used data collected from Twitter (11,14–19,21–23) or Facebook (10,12,13,20). This proportion is similar to the one found in a systematic review of literature, which found two of twelve studies used Facebook, and the remaining ten, Twitter (25). A possible explanation is that while Facebook data is richer and better suited for studying evolution of mental health over time, it is more difficult to obtain by researchers (24). Twitter appears to be the most popular platform for mental health research, followed by Facebook (26).

The main mental health condition explored by the fourteen studies is depression, explored by nine studies (12–16,18–20,23), either in isolation or along with other conditions (15,16,23). Other studies identified data related to suicide attempts (17,21), post-traumatic stress disorder (PTSD) (11,23), post-partum depression (20), or a number of conditions such as PTSD, depression, bipolar disorder, seasonal affective disorder (SAD) (16), or depression, anxiety, obsessive compulsive disorder (OCD), bipolar disorder, and panic (15). One study (10) investigated psychological wellbeing and social capital, and one study used non-specific mental illness indicators (22).

To make inferences on participants' mental health, different types of data are collected and analysed using a sequential process as described by (26):

1. Selection of social network
2. Data extraction using relevant keywords
3. Data pre-processing
4. Selection of features
5. Data classification using machine learning
6. Mental health detection.

As discussed earlier, step 1 primarily refers to the accessibility of data enabled by different platforms. The 'data' extracted in step 2 primarily refers to the textual data included in tweets or Facebook posts, which is central in the studies included in this review. Data pre-processing refers to the erasure of details that could compromise anonymity, data cleaning such as removal of slang words (22) or typos. In many cases, study design incorporates additional features (step 4), which requires the inclusion of other types of data beyond textual. This includes: usage patterns – number, frequency or time of tweets or posts (16,18,19,22); engagement or interaction with the social network (14,18), emotions or linguistic style (18–20). Different types of data are classified using machine learning (step 5), often using sentiment analysis (15) which, in the case of language, often involves the identification of positive and negative emotions (14,17,18,20). The final step, mental health detection, is achieved by considering all these classifications together.

However, pending on the study design other steps may be included related to the desire to establish the 'ground truth' needed for 'cross-verification' or calibration. In addition to the social media data, six studies used linkage to survey data which included well-validated mental health scales (10,12,14,18,19,23) which generally adds to the robustness of the findings. Some researchers found a high-degree of convergence of mental health measures derived from social media data and survey data (19), while others found more modest associations (12). A limitation of the remaining studies is the lack of cross-verification measures, which makes it hard if not impossible to verify whether the researchers' efforts to derive a mental health measure from social media data identified genuine mental health conditions.

Social media data obtained from well-known groups (i.e. longitudinal cohorts) can enhance researchers' understanding of human behaviour and how a person's mental health changes over time. Building on this opportunity, a project led by researchers Dr Oliver Davis and Dr Claire Haworth from University of Bristol is currently developing a framework for linking and sharing social media data for high-resolution longitudinal measurement of mental health across CLOSER cohorts (27). The framework will engage with participants in the Avon Longitudinal Study of Parents and Children (ALSPAC), aiming to obtain a dataset of information derived from Twitter in this cohort and develop an open-source software for secure linkage, archiving and sharing of information derived from Twitter (27). The project aims to provide proof-of-concept for other cohort studies.

Politics and the public sphere

The study identified eleven studies that used social media content related to public communication and engagement within the public sphere (28–38). One study used Facebook (29), and the remaining ten, Twitter (28,30–38).

Five studies analysed users' engagement to political parties or politicians' social media discourse (29,31–33,35), often during campaign (31–33,35), and sometimes touching on aspects such as voting intentions or polarization (35). The studies are situated within different contexts: the political sphere in Poland, as described by Facebook users' activity on the pages of political parties in periods with no major political events or campaigns (29); Twitter reactions to major party candidates during the US gubernatorial election of 2011 (31), or presidential elections of 2012 (32); Twitter engagement to the three main parties in the UK General election of 2010 (33); or Twitter reactions during the Italian constitutional referendum of 2016 (35).

Three studies explored public engagement with *citizen movements* (28,30,37). This includes a public initiative to remove certain representatives from the Mexican Chamber of Senators (28), an anti-fascist demonstration in Malmo, Sweden (37), or the immigrant rights 'not1more' campaign in the US (30). Three studies explored Twitter activity during - or related to - *public crises*, including the 2011 riots in London and Manchester (34), the 2011 protests and revolution in Egypt (36), or the former Brazilian president's trial in 2018 (38).

All studies use keyword searches to obtain their dataset of public posts - most commonly, tweets retrieved using hashtags, or Facebook posts - extracted within the timeframe relevant to the research question. The shortest timeframe in the dataset was one day, retrieving 634 posted in the day of the Malmo demonstration (37), and the longest one is twenty months, which retrieved over 108K tweets posted after the launch of the 'not1more' hashtag (30). Studies with a broader scope such as (33) retrieved over 1,150,000 tweets from 220,000 users.

The dataset of tweets or posts is analysed using content analysis, which often uses *sentiment analysis* (32–34). Researchers identify patterns of language relevant to their investigation such as ‘emotional language’ (37), trait and personality lexicon (32) or lexicon related to political participation, i.e. ‘march’, ‘blockade’, ‘demonstration’ (30). Almost half of the studies use *social network analysis* to explore the structure and direction of communications (28–30,36,38) or dimensions of social capital (38). One study also considered geographical proximity data derived from the self-reported users’ profile (30). Studies also consider aspects related to *engagement*: likes, comments or posts on Facebook (29), or tweets, retweets and replies on Twitter.

Only one of the eleven studies included data derived outside social media: a follow-up survey sent to Twitter users identified in an earlier stage of the study (31). This suggests that, while social media presents an unprecedented array of opportunities for political science research, more work is required for cross-calibration of results.

Social capital

Five articles in the review addressed aspects related to social capital (39–43). This surprisingly low number resulted from the difficulty of identifying studies that used social media data directly, instead of self-reported data about the use of social media obtained via surveys, interviews or focus groups. This led to the exclusion of widely cited studies often conducted on large samples.

Four of the five studies used Facebook (40–43) and one used the online location-based social networking site Brightkite (39). The studies vary considerably in scope, methods and sample size.

Two studies adopted *ethnographic methods*. One of them explored aspects of intimacy and social capital on a sample of 6 participants during a 12 week period in which the researcher had access to participants’ Facebook profiles (41). The other study explored the levels of interaction between Facebook friends for two samples based in the UK (n=21) and India (n=30), during a period of fifteen months of direct observation of the respective communities (42).

Two studies explored the relationship between online and offline social capital by investigating *geographical proximity*. One of them, a large-scale study conducted on approximately 1,000 university students in Copenhagen (‘Copenhagen Networks Study’), explores social interactions and human mobility by combining data obtained from questionnaires, Facebook, mobile sensing, and WiFi networks (43). The other study analysed travel behaviour and destination choice in relation to friendship networks in Chicago using data from a location-based social networking platform, Brightkite on a sample of over 1,300 users (39).

Finally, one study explored the *reciprocal nature of social capital* by observing users who were tagged by their friends on a New York Times Facebook page and analysed the response to the tagging activity (likes or comments); 4,666 posts and 418,580 comments were analysed (40).

The methodological diversity of the studies discussed in this section suggest that social media data has good applicability to the study of social capital. However, unlike the studies addressing mental health or politics and the public sphere, the articles addressing social capital rely less on textual data mining, and more, on the observation of interactions in the online (40,41) or face-to-face world (39,42,43). Three studies included data obtained from direct observations and interviews (42), surveys (43) or geo-spatial data (39,43).

Summary: Empirical use of social media data, platforms being used and linkage to other data sources

Figure 2 collates two of the key features of the thirty studies included in this review across the three areas of interest: social media platforms used in the studies, and the inclusion of other data sources in addition to social media.

Twenty studies used Twitter (11,14–19,21–23,28,30–38), nine used Facebook (10,12,13,20,29,40–43), and one study used a different platform (39). When taking area of interest into account, potential patterns are revealed. Twitter was used by articles addressing mental health, and politics and public sphere (ten studies each), but not by any of the studies with a social capital scope. In contrast, Facebook was used by mental health and social capital studies (four studies each), but only once among studies that addressed politics and the public sphere.

Figure 2. Summary of the studies included in the scoping review (n=30): Social media platforms and Data sources

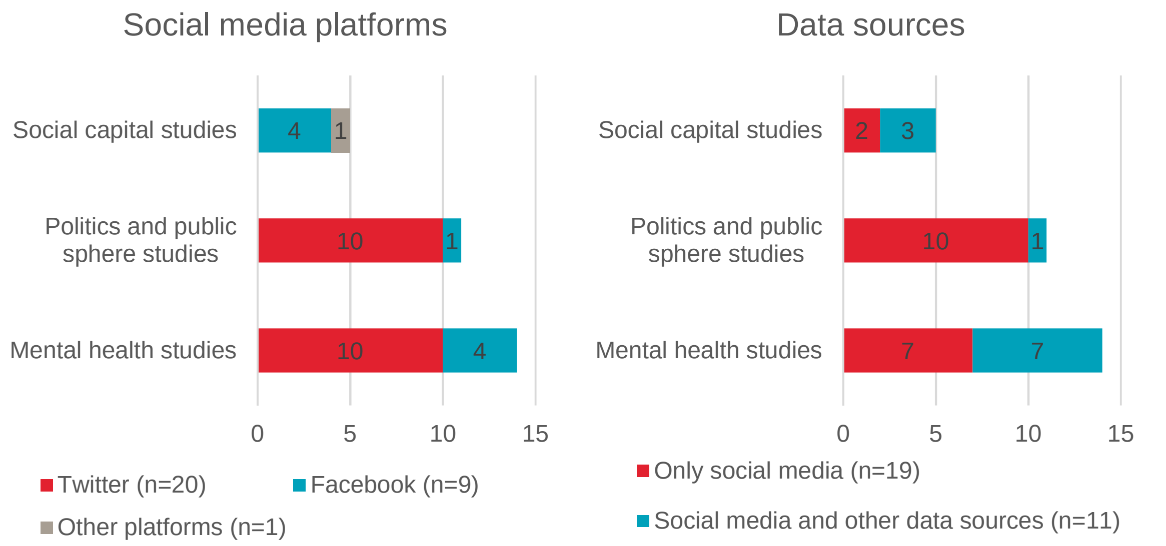


Figure 2 also shows how many studies across the entire dataset incorporated other data sources apart from social media. Overall, most of the studies included in the dataset (n=19 or 63%) relied solely on social media data; just over a third (n=11) incorporated additional data sources. The studies that did use additional data mostly addressed topics related to mental health and social capital. In contrast, almost all of the articles exploring politics and the public sphere analysed only social media data, primarily Twitter. Some of the researchers who studied mental health explicitly chose not to include surveys, to avoid limitations related to size (number of respondents) and scope (items that can be measured) (11,16). Others used surveys to administer existing scales – e.g. the CES-D – which yielded results used for calibration of social media data (19)

Using social media for social research: methodological challenges in linking social media and survey data

As shown in the previous section, most of the studies included in the review relied solely on social media data without linking it to surveys. As a result, few studies cross-verified their findings with external datasets or captured demographic information. While this scoping review is not an exhaustive exploration of all empirical research using social media, it invites reflection on the value of using surveys in *addition to* data derived directly from social media as an opportunity to address the following limitation of using social media data on its' own:

1) The limited representativity of social media data for wider populations; and

2) The issues around the validity and reliability of measures derived from social media data

Self-declared information on age, sex, or occupation can be derived by researchers from publicly available Twitter or Facebook profiles, but in the absence of 'ground truth'[6] data researchers cannot be sure if the data is genuine, and therefore, if their demographic projections are accurate. Moreover, it is often difficult to accurately derive these demographic characteristics from user profiles, particularly on Twitter. Furthermore, the population active on the various social media channels may not be representative of the wider population (44). These issues can be addressed by linking social media data to survey data obtained using random probability sampling. For example, a recent study explored the age, sex, and occupation of UK Twitter account owners[7] by reporting on a data from the British Attitudes Survey 2015 (BSA15) (44). The study found discrepancies between the population of Twitter users and the wider UK population: Twitter users were more likely to be male and younger and work in managerial, administrative, and professional occupations (44).

Most social media users (presumably) communicate genuinely and to the best of their knowledge and abilities, however "social media streams are awash in biased, unreliable, unverified subjective messages" (45) (:344), which questions the genuine nature of the data derived from it. What is perhaps most relevant for the present study is the *deliberate* nature of online self-presentation. People use a variety of strategies in order to present themselves in the best possible light and manage their 'online reputation' (46). While the desire to impress is certainly not unique to social media:

> *Offline reputation management occurs more spontaneously and in the moment, whereas online reputation management is a more conscious, premeditated, and goal-driven type of engagement, in which information is edited, filtered, and modified* (46) (:76)

The linkage of longitudinal survey data obtained from social media users may help establish the differences and commonalities between their 'virtual' and 'real-life' selves and shed light on unexplored dimensions of their lives, such as mental health, political beliefs or social capital. For example, Curtis Jessop, Research Director at the National Centre for Social Research (NatCen) illustrates how linking survey and social media data can enhance the understanding of society (47). In a study of the voting behaviour related to the UK 2017 General Election, the researchers used data from the NatCen Probability Panel in July 2017 (n=2184), and tweets from a group of respondents who agreed to share their Twitter handle (n=150; 7,555 tweets posted for 3 months before the election). While the survey collected data on voting behaviour, political preferences and socioeconomic characteristics, the Twitter data provided information about what people were talking about in the context of the election. Among other things, the linkage shed light on the success of some parties among people who hadn't voted previously.

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[6] Ground truth is defined as "a known (rather than estimated) individual characteristic" (44)

[7] In 2015, the BSA respondents – British residents, aged 18 or over – were asked whether they have a personal Twitter account.

Linking social media data also poses some specific challenges for researchers regarding *Informed Consent, Disclosure, Security, and Archiving* (48). These are discussed below.

Informed consent

In the context of social surveys, and in particular longitudinal studies, researchers may have the advantage of being already in contact with participants, increasing the chances of obtaining consent to link the social media. Direct contact seems to be the most successful mode of asking for consent to link social media data. While Twitter linkage consent rates were generally low among participants of three large representative surveys of UK adult population (27.1% to 36.8%), face-to-face surveys obtained higher rates of consent than online approaches (49). Within the 10th wave of the *Innovation Panel* sample of the *Understanding society* survey (50), overall Twitter linkage consent rates (among the 20% of the sample who declared to have a Twitter account) were 33.3%. Of the 171 who consented, 108 were asked for consent via computer-assisted personal interviews (CAPI), compared to the 63 who were asked via web surveys (50). A key element of asking for informed consent is full transparency over the type of data being linked, the purposes of collection, data security and participants' rights to withdraw their consent (48).

Data disclosure, Security and Archiving

A comprehensive list of data disclosure risks in the context of linking Twitter and social media data is provided by (47), however a prerequisite of limiting these risks is the thorough understanding of the technical and operational parameters governing the collection, provision, storage, and security of data. A variety of social media collection tools are available for Twitter (48) and other social media platforms (51), as summarised in table 5 in the Appendix.

Four principles are considered essential for maintaining data security (48) as shown below in Table 3: (1) systematic processing of data; (2) data reduction; (3) controlled access; and (4) data deletion.

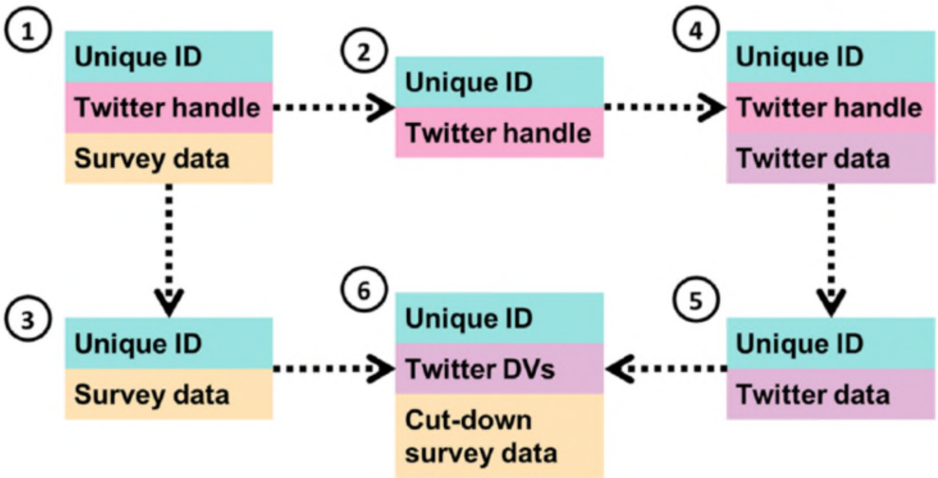
Table 3. Principles for Maintaining Security (Linked Twitter and Survey Data) Based on (48)

Principle	Description
1. Systematic processing	As much as possible, data should be managed in a systematic and considered manner. Based on the processes used for linking survey and administrative records (Administrative Data Research Network, 2018), once initial consent has been collected, survey data and Twitter data should be stored and processed separately until data linkage is required, to help control access and minimize the risk of disclosure.
2. Data reduction	To conduct analysis for any given research question, it is likely that not all of the available survey and Twitter data need to be linked together. As such, only the survey and Twitter data necessary for analysis should be made available for linkage. For the survey data, by only linking the answers required, we reduce the amount of information that may be linked back to an individual person, and therefore the risk of harm. For the Twitter data, reducing the linked variables may reduce the ease with which someone with access to the data might be able to identify a person. Should the "high-risk" variables be excluded from the linked analysis then the risk may be reduced substantially. As well as reducing the number of variables linked, data reduction may take the form of the creation of derived variables. For example, while the

Principle	Description
	analysis may require raw Tweet content initially, the linked analysis may only require a derived variable indicating whether or not a Tweet contained a reference to a particular topic, which is less likely to be individually identifiable.
3. Controlled access	Throughout the data management process, access to identifiable data should be limited to those who need it to minimize the risks of disclosure. The linked data should be held securely, so that access is granted only to those who need it, and those people with access should be documented and have appropriate training for working with identifiable data.
4. Data deletion	Data should only be held for as long as is necessary for analysis to be conducted. Once the project is complete, as with other forms of personal data, data should be securely deleted and archived if necessary.

Based on these principles, the diagram in figure 3 below illustrates a data flow designed to preserve anonymity when linking Twitter data to surveys. The two streams of data (survey and Twitter data derived from the Twitter handle) are assigned a unique ID by the researcher and separated. The unique ID is the only element that can match them together.

Figure 3. Data flow diagram for linking survey and Twitter data. Source: (48)



As per the fourth principle, archiving of data should only be done for as long as necessary. For Twitter, specific conditions apply that limit “sharing of data sets larger than 50,000 Tweets beyond the user (or their research team) who initially access the data” (48) (: 9). However, researchers may archive tweets and user IDs and use them as “dehydrated” data to query the API and access new raw data (“rehydrating”). Moreover, it is often impossible and impracticable to fully anonymise social media data, and as such challenges around onward sharing of linked social media data for secondary research.

Ethics of social media research

There are four key areas of concern related to the ethical aspects of conducting social media research: the *private / public* nature of the data; the issue of *informed consent*; *anonymity*; and *risk of harm* to participants (4). Whether social media data are *public or private* – and whether *informed consent* is required - is partly determined by the accessibility of data and the users’ expectations for privacy i.e. the terms and conditions signed by the users when using the platform. For example, a Twitter discussion including people's attitudes, often using hashtags, can be considered public, while a discussion on a password-protected (i.e. closed) Facebook group, can be considered private (4). However, '*Just because it is accessible doesn't mean using it is ethical*' (boyd, 2010 cited in (52). Direct quotations from social media cited in research can be easily traced back to their original author using a search engine, endangering their *anonymity* (52). The 'right to withdraw' aspect of *informed consent* becomes problematic: '*Does deleting a post or account equate with a withdrawal from research, and is a researcher aware when this happens*?' (4: 6). Finally, the nature of social media has increased the vulnerability of groups and individuals and the increased risk of harm. Social media users express concerns over their privacy, protecting the identity of their family and friends, their reputation and safety online (52).

Ethical considerations of research should balance these concerns with the need to advance understanding of human behaviour using the unprecedented opportunities provided by social media. To build – and maintain – participants' trust, researchers should communicate openly and transparently, explicitly stating the privacy and security aspects of research, what data are used, and for what purposes (52).

Conclusions

Social media data provide novel opportunities to advance the understanding of human behaviour and society through research. Widely used platforms such as Twitter or Facebook enable social researchers to gather naturally-occurring data on a range of subjects including mental health and wellbeing, political preferences and public opinion, and social capital. However, along with new opportunities, research methodologies involving social media introduce includes new challenges and threats.

This scoping review was conducted to identify some of the key methodological advantages and limitations of social media use for social science research, particularly linking social media data for large-scale surveys, particularly longitudinal studies. Based on academic database searches, the review identified thirty empirical studies that used social media data to explore phenomena related to mental health, politics and the public sphere, and social capital. Key findings include:

- Two thirds of the studies used Twitter (n=20), and the rest, Facebook (n=9) or a location-based social network (n=1).
- Most studies relied solely on social media (n=19), which limits the validity of the findings; the studies that used additional data sources employed surveys, interviews, spatial proximity data, or direct observation.
- Content analysis - the systematically labelling of language data – was the most frequently used method in the entire dataset, which often involved sentiment analysis, and machine learning.
- Social network analysis - the mapping of relationships between individuals, organisations or other actors - was the second most frequently used method.

Social media can cast a new light on human behaviour or attitudes towards aspects of contemporary life. Yet, social media data is not representative of the wider population: however popular some platforms may be at a certain point in time, the 'UK tweeting population' is just a sub-sample of the UK population. Furthermore, in the context of 'online reputation management', social media data is not always genuine, as users prefer to present themselves in particular ways on social media. To overcome these limitations, social media data can be linked to survey data obtained from large-scale surveys and longitudinal studies which use random probability sampling and are representative of the population.

Linking social media data to survey data faces new challenges related to research ethics, obtaining informed consent, and data security. These can be overcome by maintaining full transparency with research participants and thorough planning of the research process, including separation of survey and social media data streams, reduction of the data being collected, protecting access to the data, and discarding the data after it is no longer needed.

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Appendix

Table 4. Social media: types, examples and definitions. Based on (1)

Type of social media	Examples	Definitions
Social networking sites	Facebook, LinkedIn	'Web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system' (boyd and Ellison, 2007: 211)
Bookmarking	Delicious, StumbleUpon	'Provide a mix of both direct (intentional) navigational advice as well as indirect (inferred) advice based on collective public behavior. By definition – these social bookmarking systems provide "social filtering" on resources from the web and intranet. The act of bookmarking indicates to others that one is interested in a given resource. At the same time, tags provide semantic information about the way the resource can be viewed' (Millen, Yang, Whittaker, and Feinberg, 2007: 22)
Microblogging	Twitter, Tumblr	'Services that focus on short updates that are pushed out to anyone subscribed to receive the updates' (Grahl, 2013: n.p.)
Blogs and forums	LiveJournal, Wordpress	'Online forums allow members to hold conversations by posting messages. Blog comments are similar except they are attached to blogs and usually the discussion centers around the topic of the blog post' (Grahl, 2013: n.p.)
Media sharing	YouTube, Flickr, Pinterest	'Services that allow you to upload and share various media such as pictures and video. Most services have additional social features such as profiles, commenting, etc.' (Grahl, 2013: n.p.)
Social news	Digg, Reddit	'Services that allow people to post various news items or links to outside articles and then allows it's users to "vote" on the items. The voting is the core social aspect as the items that get the most votes are displayed the most prominently. The

Type of social media	Examples	Definitions
		community decides which news items get seen by more people' (Grahl, 2013: n.p.)
Collaborative authoring	Wikipedia, Google Docs	Web-based services that enable users to create content and allow anyone with access to modify, edit, or review that content (Archambault et al., 2013)
Web conferencing	Skype, GoToMeeting, Zoho Meeting	'Web conferencing may be used as an umbrella term for various types of online collaborative services including web seminars ("webinars"), webcasts, and peer-level web meetings' (Web conferencing, n.d.)
Geo-location based sites	Foursquare, Yik-Yak, Tinder	Services that allow its users to connect and exchange messages based on their location
Scheduling and meeting	Doodle, Google Calendar, Microsoft Outlook	Web-based services that enable group-based event decisions (Reinecke et al., 2013)

Table 5. Social media research tools for 2019. Source: (51)

Tool	OS	Download and/or access from	Platforms*
Audiense	Web-based	https://audiense.com/	Twitter
Brand24	Web-based	https://brand24.com/features/#4	Twitter, Facebook, Instagram, Blogs, Forums, Videp
Brandwatch	Web-based	https://www.brandwatch.com/	Twitter, Facebook, YouTube, Instagram, Sina Weibo, VK, QQ, Google+, Pinterest, Online blogs
Chorus (free)	Windows (Desktop advisable)	http://chorusanalytics.co.uk/chorus/request_download.php	Twitter
COSMOS Project (free)	Windows & MAC OS X	http://socialdatalab.net/software	Twitter
Echosec	Web-based	https://www.echosec.net	Twitter, Instagram, Foursquare, Panoramio,

			AIS Shipping, Sina Weibo, Flickr, YouTube, VK
Followthehashtag	Web-based	http://www.followthehashtag.com	Twitter
IBM Bluemix	Web-based	https://www.ibm.com/cloud-computing/bluemix	Twitter
Keyhole	Web-based	https://keyhole.co/	Twitter, Instagram, Facebook
Mozdeh (free)	Windows (Desktop advisable)	http://mozdeh.wlv.ac.uk/installation.html	Twitter
Netlytic	Web-based	https://netlytic.org	Twitter, Facebook, YouTube, RSS Feed
NodeXL	Windows	https://www.smrfoundation.org/nodexl/	Twitter, YouTube, Flickr, Wikipedia
NVivo	Windows and MAC	http://www.qsrinternational.com/product	Twitter, Ability to import
Pulsar Social	Web-based	http://www.pulsarplatform.com	Twitter, Facebook topic data, Online blogs
Social Elephants	Web-based	https://socialelephants.com/en/	Twitter, Facebook, Instagram, YouTube
Symplur (Healthcare focus)	Web-based	https://www.symplur.com/	Twitter
SocioViz	Web-based	http://socioviz.net	Twitter
Trendsmap	Web-based	https://www.trendsmap.com	Twitter
Trackmyhashtag		https://www.trackmyhashtag.com/	Twitter
Twitonomy	Web-based	http://www.twitonomy.com	Twitter
Twitter Arching Google Spreadsheet (TAGS) (free)	Web-based	https://tags.hawksey.info	Twitter
Visibrain	Web-based	http://www.visibrain.com	Twitter
Webometric Analyst (free)	Windows	http://lexiurl.wlv.ac.uk	Twitter (with image extraction capabilities), YouTube, Flickr,

	Mendeley, Other web resources