Artur Pokropek
IFiS PAN

Project Description
Research Lab for the Digital Social Sciences

1. The aim of the project

This project aims to advance methods to use online trace data (called also digital footprints) together with survey data and thus, will contribute to solving current social problems concerning trust, attitudes towards migration, environment, governments as well misinformation and polarization of attitudes. We share a believe that the analyzing online trace data can provide better insight into human interests, attitudes, behaviors and will be proven valuable in examining behavioral changes by allowing researchers to investigate long series of outcomes of interest measured with extreme frequency (even every day or every hour). Digital trace data could be also useful to investigate diversity between geographical regions (e.g., NUTS 5, small cities) for which, because of the sample size limitations, representative survey data are usually not available. Digital footprints, because of their cost efficacy, are irreplaceable in large scale network analysis where traditional survey approach has serious methodological and financial limitations not allowing to reach all members of the network. Moreover, digital trace data are good device for cross-validating results provided by the surveys bringing another angle of view and strengthening or falsifying research hypothesis. Finally obtaining digital trace data is incomparably faster than traditional survey methods which was clearly seen in current pandemic situation. Even the best, most rapid, and coordinated responses of classical surveys like COVID-19 Snapshot Monitor (Betsch et al., 2020) was only launched several weeks after the pandemic had been declared. This is good example because it reveals also other shortcomings of such mode of the research. The Snapshot Monitor was providing information on a weekly basis, was limited to 10 waves and only 500 respondents per country. On the other hand, information from social media platforms (Twitter, Facebook, LinkedIn, etc.) where people express their opinions is available with hourly precision, providing millions of observations in various social groups, in different cultures and countries and through continuous, practically unbounded periods of time.

Without a doubt, surveys provide much important information and are extremely useful and necessary in monitoring public opinion, because online data sources will always lack the precision of operationalization and the theoretical orientation that can be provided by classical surveys. However, we claim that, by using both online and offline data sources with proper methodology and within a cross-country perspective, we could provide additional value and complementary information on people's attitudes, behavior, knowledge, and health, information that is useful in understanding social word. This, however, will not happen without a serious methodological work on online data and without help of more traditional data collection modes, e.g. provided by surveys. Following (Salganik, 2019) we believe that online data will not eliminate the need to directly ask people questions in surveys but will substantially enhance the usability of surveys in big data analysis allowing for calibration, cross-validation and for checking crucial assumptions made by online big data. Properly handled online big data facilitated by classical instruments could help researchers to address fundamental questions of social science. As pointed by Golder and Macy *over the past century, there has been no shortage of social theory, but there have been severe constraints on access to data* (2014, p. 130). Unprecedented opportunities related to online big data collected on massive scale yet on micro level might change this position.

To advance methods to use online trace data we propose to run large methodologically oriented study that will utilize five sources of data: (a) representative survey data, (b) online trace data, (c) data form specially designed panel study that will combine survey and online trace data, (d) experimental studies and (e) qualitative data. In big picture, we will ask several research questions (on trust, attitudes towards migration, environment and governments, misinformation and polarization of attitudes), answer them using difrent sources of data and compare the results. This allows us to understand shortcomings and problems of different approach and develop new methodological means to excel the inference on sociological questions. We have had decades of methodological work to improve how carry out surveys and how to properly use survey data. We need to invest in methodological developments of online data to better leverage its potential and disclose its limits and understand how they could enrich our knowledge.

2. Background and the importance of the project

Technological development has moved a substantial part of human life towards the computer or/and smartphone screens changing noticeably some of the human behaviors and inducing new ones (Bauman, 2013; Hynes, 2018; Jinasena, 2014; Thompson, 2013). The way how people, communicate, interact and search for information has dramatically changed in this digital transition. In year 2019 around 4,2 billion people are using the Internet on a daily basis. That is 54% of world population and 87% population from the developed world (International Telecommunication Union, 2019). The intensity of digital technology usage is growing fast. It is estimated that in 1992 the total amount of Internet traffic was around 100 gigabytes per day. This number increased by a factor of 17.5 million in 2017. Around 90 percent of the data in 2017 was generated in the prior two years (Nadella, 2017). People relay on digital technology in more and more areas of life. In year 2017 Google Drive was used by 800 millions monthly active users (that is more than 15% of word's population) with three billion objects and 1.2 billion of photos uploaded each day (Schmidt, 2017). Google in 2020 processes over 40,000 search queries every second on average, which translates to over 3.5 billion searches per day and 1.2 trillion searches per year. Worldwide average internet user is asking their devices different types of questions roughly 2 times a day. In USA the average adult checks his or her phone 30 times a day, while for adolescent this number reach 157 times daily (Zuboff, 2019). In UK adults spend more than half of their working hours engaged in media or communication activities, and that time has doubled over the past decade (Ofcom, 2015). More than 99% of respondents between 16 and 54 has a mobile phone, and more than 80% of respondents between 16 and 44 have a social media profile. Online behaviors including social interactions have become are regular part of daily life for billions of people worldwide.

Most of these behaviors are recorded and stored as fine-grained time-stamped data at the individual level available for millions or billions of users. Such amount of data is unpresidential for social science and could be compared only which enterprises like particle accelerators or genomic studies in natural sciences. For some researchers newly developed tools for observing online activity showing promise to have a similar transformative effects for social sciences to electron microscope, space telescope, particle accelerator, and magnetic resonance imaging in natural (Golder & Macy, 2014) underling the fact that revolutions in sciences could be initiated new tools and methodologies (Kuhn, 1962). This point of view is usually not shared by researchers from the field of public opinion, survey methodology or more broadly social science methodology. In those fields researchers have ignored, to a large extent, online data revolution. Not without a reason. Online data has been considered as a black box, which limits possibilities to delve into a problem, which, in fact, resulted in or was found to be the reason of several spectacular failures of this approach (see next sections).

2.1 The problem: How to collect the data?

In general, there are two ways of obtaining empirical information in social sciences. The first is to observe people and their behaviors. The second is to ask people about their behaviors, feelings and opinions. Both have been applied in qualitatively and quantitively oriented studies, for experimental and non-experimental designs. The problem with both approaches is that people tend to behave differently when they are under investigation. We don't talk here about "big lies" or even fully conscious attempts to mislead the research (which definitely also happens) but rather the simple fact of social behaviors. Most people under examination are trying to make their best and usually, want to do what other people expect them to do (Fisher, 1993; Fisher & Katz, 2000).

Social scientists are not helpless in dealing with these problems. In fact, many procedures and statistical models were developed to cope with the complex human nature of respondents. Researchers often try to 'trick' respondents by disguising the real object of observation in the research. For example, in the social psychology experiments real goals of the study are presented usually at the end (Aronson et al., 1990). In survey research, special control items are added to the questionnaire that aims to detect untruthful responses, e.g. overclaiming items (Paulhus et al., 2003; Phillips & Clancy, 1972), lie-scales items (Eysenck et al., 1974), reverse coded items or response time is registered to detect careless responses (Baumgartner & Steenkamp, 2001). Finally, statistics offers various modeling techniques (mixture modeling, IRTree models, process data modeling) to adjust the results for different response styles (Khorramdel & von Davier, 2014). But this is always the struggle, the secret war between those who are watched and those who are watching where the final result is always uncertain.

2.2 Digital Footprints: a well-designed trap or source of endless possibilities?

The supposed solution that has a potential to ensure more accurate information about human behaviors side lies in the high resolution, presumably non-reactive nature of big data that captures real-life behaviors and in the analytical approaches using machine learning tools. Big data advocates have been suggesting that data digital traces are especially suited for social science research. Good example is data from search engine queries. First, they are anonymous. Sometimes techniques that used search data are referred to as "digital true serum" (Stephens-Davidowitz & Pabon, 2017) anonymity implies truthfulness. Second, search queries can be considered real-life behaviors. People entering the search queries usually do not consider themselves as being observed by researchers and are motivated by their own purposes. Next, access to this data is fast and they are collected continuously which means that some rapid social phenomena might be analyzed even if social scientists were not prepared for monitoring them allowing to compare some indicators before and immediately after a social event. Finally, those data is non-reactive. This implies that the process of measurement in big data sources is much less likely to change behavior than classical types of data collection (Salganik, 2019).

Probably the most well-known application of search data is Google Flu Trends (Cook et al., 2011). Google engineers developed the algorithm based on search queries and historical data from Centers for the Disease Control and Prevention (CDC) to predict flue trends in real-time. The idea was simple. Sick persons will search for information about flu symptoms or treatments more often than healthy people. The increase in volume of flu-related queries should be related to the actual flue trends. As machine learning tools are very good at finding relations between different variables, it is possible to establish the relations between past internet searches and past real epidemiological data. After that, predictions of current flu trends based on current search data can be made. This solution is much faster than real data collection (which takes even weeks) and of course much cheaper as the data are already there. The story about smart use of 50 million of the 45 most commonly used search queries to establish general flu activity was commonly used as an example of innovations that moved our society towards technology-dominated future (Harari, 2016), often presented as a real big data success in many books (Mayer-Schönberger & Cukier, 2013). What those books do not usually tell you is that the GFT exercise was a complete failure (resulting in closing of the project) because of its incapability to detect real flue pandemics. The project which replaced it and is supported by CDC - "Flu Near You" (https://flunear-you.org) – is more or less based on classical online survey methodology (Chunara et al., 2013). In fact, some methodologist are joking that the initial version of GFT was so bad that it could be called part-flu-detector-part-winter-detector (Lazer et al., 2014). In the end, Google Flu Trends was not much better than that of a simple model that estimates the amount of flu based on a linear extrapolation from the two most recent measurements of flu prevalence (Salganik, 2019). The example of GFT clearly shows that although the idea of using search data in research applications is appealing much more work must be to use it in a meaningful way.

Despite the spectacular failure of the GFT in epidemiology, studies using internet search data have been conducted in the social sciences. Ettredge, Gerdes, and Karuga (2005) used internet search data to forecast the unemployment rate in the US and that line of research was continued by other scholars (Askitas & Zimmermann, 2009; Baker & Fradkin, 2017; Choi & Varian, 2009). Webb (2009) used search data to examine US home foreclosures. Carrière-Swallow and Labbé (2013) examined trends in consumptions. Algan, Murtin, Beasley, Higa, and Senik (2019) used search data to study well-being and Stephens-Davidowitz (2014) – to study the role of racism in US presidential elections. In the field of consumer behavior research outcomes like opening weekend box-office revenue for feature films, first-month sales of video games, and the rank of songs on the Billboard were predicted using the volume of people searching for the selected phrases (Goel et al., 2010). Mavragani, Sypsa, Sampri, and Tsagarakis (2016) used search data to measure public interest in micro pollution policy. The above-mentioned studies are only a humble subsample of the much larger population of search engine-based studies. Although some attempts were more successful than others, the common denominator of these studies is that search engines data, as well as predictive statistical models, are treated as black-box devices to provide the desired numbers in an almost magical way without much understanding how these numbers are created.

It is surprising how little methodological concern was put into research on search data. How many questionable assumptions were taken as granted, hidden or treated as an advantage (rather than a problem)? Let's consider the first supposed advantage. People feel that searches are anonymous and private. This assumption is flawed at the very basis. Search engines like Google collect and store records of every search made to analyze individual searches and based on that deliver user data across the services they provide. Even if the awareness of these practices is rather low (Fuchs, 2017; Tsay-Vogel et al., 2018) , we might expect that privacy concerns might grow and more importantly be unequally distributed across different social groups introducing different selection procedure of searching behaviors for different social groups (Zuboff, 2019). Next, there is an assumption that everyone is googling. In other words that all kinds of people search the internet for similar purposes and in similar way and consequently, that the searching behavior is common and universal. This is far from obvious. Stephens-Davidowitz and Pabon (2017) give an interesting example on the contrary. When we look at Google search data from the US, there are twice as many complaints that a boyfriend won't have sex than that a girlfriend won't have sex. How should we interpret this? Could we really conclude that boys have less desire to have sex? Probably not. Or maybe those two groups distribute their questions about sex not only to internet search engines but also to their friends? Maybe girls don't like to talk about sex with their friends while boys don't have problem with complaining to their mates? Maybe boys look up for the answers more often in books? Maybe girls look at books more often and the difference is not two times but four times bigger? The simple answer is we don't know.

Similar concerns and problems are related also to other sources of internet data. Because of space limitation we refer only to two examples and citing only the title of the articles: *It's Not That I Don't Have Problems,* *I'm Just Not Putting Them on Facebook: Challenges and Opportunities in Using Online Social Networks for Health* (Newman et al., 2011) and *Why the Pirate Party Won the German Election of 2009 or The Trouble With Predictions* (Jungherr et al., 2012).

3. Concept and research plan

3.1 Research objectives

Researcher in the pursuit of answers for some substantial questions needs to solve series of methodological problems that allow him or her to properly test posted hypotheses. Methodological issues, despite being important, play always a secondary role, with the primary role of theory. The research program stated in this proposal is unique in this respect. In this project methodological questions drive the pursuit for knowledge about substantial problems. In this project, we want to treat methodological and substantive problems with equal attention believing that this will contribute to better understanding of human online behaviors in the modern world.

The three main objectives of the proposed research are (1) Understand online behaviors. Who is using which digital platforms? What platforms are used and how? (2) Develop mixed, "hybrid", methodology of joint use of the digital traces and survey data. (3) Develop applications for key social challenges concerning: (a) generalized trust, (b) political efficacy, (c) general health, (d) attitudes towards migrants, and (e) attitudes towards climate change and contextual research topics (a) misinformation and (b) polarization of attitudes.

The detailed overview of the project objectives, main methods and rationale for the proposed actions are presented in Table 1. First of all, we want to learn more about digital platforms and their impact on social life. There is a lack of comprehensive sociological research in this topic and sociological knowledge about this behavior is limited. With this proposal we would like to provide robust evidence on how digital platforms changed contemporary social life, how it affects traditional social sources of information (family, friends) and social relations connected with those sources. Finally, we want to learn how different groups of people use digital platforms. What do they look up on the internet? What are the topics that are not being searched on the internet? How much do different groups of people (defined by gender, socioeconomic status, age) trust the information from internet? Could some behaviors (together with specific algorithms provided by digital platforms) increase exposure to fake news? How do personalization of algorithms provided by some digital platforms influence the exposure to information? To this end we will conduct: a) representative survey data, (b) online trace data, (c) data form specially designed panel study that will combine survey and online trace data, (d) experimental studies and (e) qualitative data (cognitive interviews).

Table 1. Main goals of the project

WHAT? Objective	**HOW?** Method	**WHY?** Rationale
(1) Understand online behaviors. Who is using which digital platforms? What platforms are used and how?	(a) Using qualitative and quantitative methodology including cross sectional survey, panel, observational and experimental designs.	(Ia) To understand online behaviors and how they affect opinions. (Ib) Verify the assumptions necessary for developing appropriate methodology that will utilize digital footprints.
(2) Develop methodology for hybrid use of internet search data and survey data.	(b) High density, high quality "classical" survey data confronted with information from digital platforms that use different methodologies and assumptions.	(II) To make digital trace data more useful for social science researchers
(3) Applications for key social challenges.	(c) Using developed methods based on hybrid approach combining big data with classical surveys.	(III) To investigate longitudinal dynamics and relations of selected outcomes that could not be achieved using classical survey methodology.

The work related to the second objective will allow verifying the assumptions necessary for developing an appropriate methodology for hybrid use of digital traces data and survey data. On one hand, **the idea of this project is based on a deep objection to the approach rejecting the theoretical reflection and discarding years of methodological development in social sciences reflected in end-of-theory, end-of-methodology claims** and everyday practice of some of the data scientists (C. Anderson, 2008; Prensky, 2009; Steadman, 2013; Stephens-Davidowitz & Pabon, 2017). On the contrary, we do plan to use and benefit from recent achievements of measurement theory, survey methodology and related statistical methods that have significantly improved the ability to measure wide range of social concepts. On the other hand, we recognize a significant, exciting and valuable opportunity to develop complex, wider-scale, more detailed models of human behaviors using the new data sources that were not available even a couple of years ago (Kitchin, 2014). We believe that data from search engines, blogs, microblogs, social network platforms could bring valuable information only if spatially designed "calibrating" surveys that would bring precision and validity to big data from search engines, are simultaneously applied. The core of the idea is that we will conduct larger number of high-density micro surveys (around 20 measurements in 2 years) that will give information about selected outcomes interesting from a sociological point of view and studied in this project. By having high quality data from surveys and proper measurement of outcomes under consideration we will build methodology to build similar measures using our hybrid approach. Unlike previous research on this topic using the data from search engines or Twitter we will not use solely the most predictive words, but we will use models based on theoretical assumptions and knowledge obtained from our explanatory research survey, panel and experimental studies. For instance, referring to search engines data in the explanatory phase we will investigate what are the exact words used by people to check information about climate change, who is using which words and in what circumstances the search engines are used. Moreover, we will design "calibrating" surveys (component 2) - bigger surveys that will monitor population in terms of system and usage drifts (Salganik, 2019) of search behaviors to make more valid use of search data. Similar methodology has been used in the context of survey methodology (Chen et al., 2019; Davies, 2018) but we will adapt it to the search data problems. The main aim of calibration surveys is to estimate socio-economic structure of searching behaviors that could relate volumes and types of searches to the main segments of population. The goal of this methodological work is to make digital trace data more useful and reliable for social science researchers by 1) understanding cognitive mechanisms lying on the basis of online behaviors and 2) exploring the nomological network of the socio-psychological correlates of the online behaviors.

Third objective of this study is to monitor five outcomes of relevance for social research: (1) generalized trust, (2) political efficacy, (3) general health, (4) attitudes towards migrants, and (5) attitudes towards climate change and contextual research topics (a) misinformation and (b) polarization of attitudes. High density of big data combined with precision provided by calibration surveys will allow to examine longitudinal dynamics and relations between selected outcomes that could not be achieved using the classical survey methodology. In empirical analysis that will be conducted addressing the third objective high density of digital trace data will allow to investigate impacts of rare events (e.g. voting days, protests, natural events, news etc.) that could not be achieved using the classical survey methodology and allow to investigate spatial differences in selected outcomes.

3.1 Research plan

In the project we will concentrate on two online activities (I) searching information (googling) and (II) using social media (focusing mostly on Twitter and Facebook). The project consists of three main overlapping research components that will be implemented sequentially. Each of the three components corresponds to three main objectives, builds on the previous ones and brings new scientific gains. The components constitute a hierarchical structure that will allow the examination of a series of project goals (see Table 1). All analyses will be performed in Poland and Polish data. The overview of research plan with the focus on data collection (each data collection has corresponding analytical phase) was depicted in Table 2 where 9 data collection activities describe the flow of the project.

Table 2. Overview of research plan (with the focus on data collection, each data collection has corresponding analytical phase).

What	Short description	Year	Mode	Component
(1) Designing and piloting instruments	All instruments will be pre-piloted on small samples (N c. 5x20)	**1-2**	On-line / off-line	1,2,3
(2) Cognitive interviews	Qualitative study on online behaviors (N c. 3x30)	**2-4**	Off-line	1,2
(3) Experimental studies	Experimental studies on online behaviors (N approx. 3x200)	**2-3**	On-line / off-line	1,2
(4) Exploratory survey	For examining online behaviors (N c. 1500; single representative survey or part of omnibus)	**2**	Off-line	1,2
(5) Micro surveys	20 micro surveys – monitoring social outcomes; part of representative omnibus (N c. 20x 1500)	**3-4**	On-line / off-line	2,3
(6) Calibration survey	Surveys necessary to develop hybrid methodology (N c. 3x 400)	**3-4**	On-line / off-line	2,3
(7) Panel study	Two-year study (N c. 1500)	**3-4**	On-line	1,2,3
(8) Twitter data collection	Collecting around 10 million Tweets and annotating 100k	**3-5**	On-line	2,3
(9) Facebook data collection	Data collection from Facebook (N c. 4x50)	**3-5**	On-line	2,3

4. Research methodology

4.1 Component 1: Understanding internet behaviors

The first component will rely mostly on exploratory survey research (4; see Table 2 also for further references to the data collection) and panel research. That will be preceded by piloting studies (1) and cognitive interviews (2) that facilitate proper construction of survey tools. We anticipate that, the questionnaire will be composed of 6 parts:

1) General questions about ways of obtaining various information and knowledge
2) Specific questions about using search engines, social media (using and opinions about them)
3) Questions on digital competencies
4) Questions on attitudes towards migrants, climate change, government, trust and wellbeing (from ESS and International Social Survey Programme)
5) Questions concerning ethical aspects of using big data and privacy
6) Questions about socioeconomic status and demographic characteristics

The next big empirical component is panel study (7, Table 2) designed for 2 years with multiple measurements and a missing-by-design plan (Graham et al., 2001; Pokropek, 2011). In this part history of search queries and social media usage will be collected in a two-fold manner. First, we will ask to use a designed application that will record searches and social media activities. As it is not realistic to ask respondents to participate in the research for a whole 2-year period we will use a rotated design where groups of participants will be asked to use the tracking application during selected weeks per year, in two-week blocks. After each block respondents will receive an additional short online questionnaire and small gifts and will be eligible to participate in a lottery with more valuable gifts to increase motivation to participate in the study. Second, we will apply to search engine providers and social media providers for the full register of their searchers and social media activities for the whole period of research. This task requires many angles because we want to capture search behaviors and social media behaviors on different devices (computers, smartphones, smart speakers, etc.) in different environments (home, work, etc.) and from different providers (Google, DuckDuckGo, etc.). Our approach is unique, but we will build on previous media audience research that tackle also internet media (Mytton et al., 2016) and that proved to be successful in this respect.

During the 2 years of panel study, series of experiments (3, Table 2) will be conducted. Respondents will be asked to obtain different information in different context. This will be conducted with accompanied cognitive interviews that will allow us to understand the process behind searching practices (Cizek, 2012). In experiments respondents will be asked to search for different pieces of information using different search engines or/and social media. Different context for information will be provided in different experimental groups (e.g. searching for providing information, searching for hobby, searching in scenario-based situations, etc.). The efficiency of searching will be assessed by the outcome of search findings, time and the number of steps required to obtain information. We will also ask respondents to search using their devices and provided device without history of searching to assess how personalization of searching algorithms provided by some search engines influence the searching outcomes. Both respondents that participate in panel study and those out of the panel sample will participate in a cross-validation in order to check whether participation in the panel study made any changes in the searching habits.

The first component of the project could be characterized as being low-risk and high-gain. The component will build on an existing body of methodological knowledge. The proposed research is difficult to implement. It requires many angles because we want to capture search behaviors on different devices (computers, smartphones, smart speakers, etc.) in different environments (home, work, etc.) and from different provides (Google, DuckDuckGo, etc.) but does not go beyond standard survey projects. Experience of PI who was working with serval successful cross-sectional studies (PIAAC, PISA) as well serval panel studies (FS2W, EWD panel) and rich experience of the institution where this project will be realized leaves no doubt that the proposed tasks will be fully implemented and results the results will make an essential contribution to sociological research.

4.2 Component 2: Developing methodology for hybrid usage of the digital traces and survey data

Main part of the work in this component will be dedicated to establishing proper statistical methodology for using search data and data from social media and relay on what we learn from component 1 plus form empirical data collection (points 5,6,7, 8 and 9 in Table 2).

4.2.1 Search data

The present practice of using the volume of search data is rather straightforward and was proved to provide inaccurate data. Researchers use the index of frequency of single word (e.g. suicide;(Solano et al., 2016)), or a set of *ad hoc* terms (Bakker et al., 2016) seldom explaining under what grounds the words were chosen and very often missing the full list of the terms used. Another approach is to use machine learning algorithms to choose a set of terms that are most predictive for the outcome under research like in the famous example of GFT (Ettredge et al., 2005) in which the final set of words was not revealed, either. We will test existing approaches, but the main task is to build solid methodological grounds for the selection of key terms that will be further used in the analysis of search data. More specifically we will provide:

1) Evidence-based and theory-driven selection algorithms of search phrases for predicting selected outcomes.
2) Parametric statistical models for measurement of outcomes that allow for explicit testing of assumptions of measurement and thus replacing black-box approach of machine learning tools.
3) Statistical and methodological approaches for handling heterogeneity of population in searching behaviors.

The main data collection for the second component is designed to collect a large number of data points (20) with classical surveys by placing few items in ongoing representative surveys (so-called omnibus surveys that are regularly conducted to monitor public opinion). Additionally, calibration studies will be conducted to monitor possible drifts in searching behaviors regarding specific topics (Salganik, 2019, pp. 33-37). Those studies will consist of questions on using search including a retrospective question on searching particular words. For instance, whether in last week a respondent used search engines for acquiring knowledge about climate change, security issues, political actors, etc. and in which context. This will allow assessing whether searching of particular words is invariant across time concerning the aim of measurement that is in this example attitudes towards climate change, trust or political efficacy. We will also collect information on who searches particular words to be able to correct estimations for population drifts (changes of socio-economic structure of searchers). This will be done with the panel respondent. The aim here is to finish with the proper methodology of constructing such calibration surveys that could effectively monitor and enhance search data.

To deliver evidence-based and theory driven selection algorithms of search phrases, we will utilize data from surveys, experiments and cognitive interviews from the component 1. Thanks to this we will know what phrases are used by searchers for specific problems and this will allow as to use theory-driven indicators. To cover heterogeneity of possible phrases usage, we will use natural language processing tools already used in social sciences. Specifically, we will build models based on Word2Vec methodology (Lilleberg et al., 2015) that will allow to find additional phrases similar to the meanings obtained from the empirical research to increase validity of the study.

To develop parametric statistical models for measurement of outcomes we will apply methodology known as measurement of latent variables, commonly used in educational and psychological measurement of latent traits, specifically the Confirmatory Factor Analysis (Brown, 2015). Search data will allow to obtain indexes of similarity between searched phrases (items). Those might be treated similar to correlations between search phrases and therefore open a possibility to estimate Confirmatory Factor Analysis (CFA) measurement models with all the benefits of these models refined for over half a century by researchers interested in measuring various variables. CFA allows for explicit testing assumptions of measurement like model fit, reliability, measurement invariance (Pokropek et al., 2019), and consequently replacing the black-box approach of machine learning tools.

To develop statistical and methodological approaches for handling heterogeneity of population in searching behaviors we will introduce a weighting system that will account for the diversity of modes of internet searches by different groups of respondents. The exact figures will be learnt from the explanatory survey described in component 1. This idea is not new in survey statistics (Gelman & Carlin, 2002; Park et al., 2004) but practically ignored in the context of search engine data.

4.2.2 Twitter Data

Twitter is a microblogging social media platform that allows users to share their thoughts in up to 280 characters (the average length of a tweet is 33 characters). The content of the tweet may include personal notes, humor, or opinions on current events, media, behavior, and politics. The short format of tweets encourages users to update the Twitter account multiple times per day (Java et al., 2007). Twitter represents an incredible opportunity for researching public opinion (Diakopoulos & Shamma, 2010; Golder & Macy, 2011; Reips & Garaizar, 2011; Yardi & Boyd, 2010). Research using Twitter data is not new; researchers were previously using data from Twitter to document changing moods and other sentiments. Twitter research is especially popular in political sciences: Jungherr (2016) presented the results of a systematic literature review of 127 studies addressing the use of Twitter in election campaigns. Furthermore, Twitter data have been also used in relation to health related research: tracking the spread of influenza (Achrekar et al., 2011), gathering information on the prevalence of oral health problems (Heaivilin et al., 2011), or investigating mental health (Golder & Macy, 2011). From an analytical perspective, these studies used text mining approaches, among others, sentiment analysis which estimates whether a tweet expresses a negative, neutral, or positive affective tone or topic modeling which analyzes the topic underlying a class of tweets. Therefore, similar techniques to those to be utilized in this project have been previously used (at least to a major extent), and they have been successful. However, we are proposing substantial methodological innovations.

Measurement based on data from social media will always be indirect while classical survey tools allow for direct measurement of opinions, attitudes, feelings, etc. Combining big data indirect measurement of social media (mainly Twitter in our case) with smaller but direct and precise measurement will open up new possibilities:

1) Evidence-based and theory-driven selection of phrases for predicting selected outcomes.
2) Linking online behaviors and statements (tweets) of certain social groups with characteristics, opinions, knowledge, behavior, and health measured by classical questionnaires (e.g., by examining if younger males are more critical of the measures, have more or less knowledge, and a lower compliance with the policy measures using both approaches).
3) Creating more valid indicators of public opinion, behavior, and knowledge based on Twitter data by relating information in tweets to established measurement instruments of survey methodology.
4) Reweighting Twitter data to be more representative (full reweighting will not be possible due to limited information about tweets; however, at least gender and age categories could be successfully inferred, e.g., (McCormick et al., 2017)).
5) Cross-validating results based on tweet analysis and classical survey data.

The data extraction will be based on the list of the words connected to the topics. The list of the words connected with the topic will be provided by evidence-based and theory-driven selection of phrases for predicting selected outcomes as described in part for searching. The lists of the words together with all possible grammar variations will be prepare. This methodology was previously used to collect data from Twitter (Hanna et al., 2013). In addition, for each of the languages, we prepared a list of the most popular misspellings and grammar mistakes to increase coverage of the relevant tweets. A tweet object (from the Twitter API) consists of many pieces of useful information, such as date of its creation, the unique username of the person posting it, the count of likes it received, retweets, replies, and most importantly the text, that is, the (usually) most significant content of the post. The geolocation of the person responsible for creating the tweet is sometimes also available, yet from the language of the text (also provided by Twitter API), its country of origin might be deduced as well. The full list of parameters which are obtainable from a single tweet can be found at developer.twitter.com. Besides the crucial part, i.e., the analysis of the text itself, identification of the user plays also an important role, enabling us to evaluate how individual emotions change during such an event (do note that the exact identification of the user is not necessary to measure changes in time, as it is sufficient to know that certain tweets were produced by the same Twitter account).

In order to facilitate the compilation of annotations of the tweets' content, the aforementioned portal shall be used. Approximately 20 persons will be hired to perform this task. We aim to encode 100,000 tweets, with about 5% of them annotated twice to check for inter-coder reliability. Based on our past experiences, we will prepare the portal to be both sustainable and efficient and to have a user-friendly interface. Each coder will have an individual access (via login and password) to the previously described web application, in order to answer a series of short questions for a random sample of tweets. The annotated tweets will allow us to infer larger trends, however, to link it to relevant political actions and the development of the pandemic. As a higher resolution is needed, machine learning tools combined with natural language processing (NLP) will be used to predict features of tweets that have not been coded.

Deep learning models are a form of neural networks (NN) and perform incredibly well for problems that are too complex to solve analytically, such as Image Processing, Speech Recognition, or Natural Language Processing (NLP) (Schmidhuber, 2015). Solving a NLP related problem consists of two parts: transferring the language to a form that the machine learning model can process, that is, transforming it into a numerical format, and then training it. For the first part (the transformation into a numerical format), we will use a technique called word embedding. Using the most successful word embedding systems such as Word2Vec, Continuous

Bag-Of-Words (CBOW), and Skip-Gram (SG) as well newer developments (e.g. fasttext, USE, BERTm GPT-w, GPT-3), we will be able to process the data to be feasible for the training of the machine learning model. The process of further investigation in terms of emotions in the text, is called sentiment analysis, or opinion mining (Liu, 2015), which after embedding becomes a task of numerical optimization. We are going to fulfill this task using machine learning models, especially deep neural networks, in order to predict features of the tweet content. In this step, the NN learns the relationship between the labeled data and characteristics of the text. This is mostly utilized using deep variations of Recurrent Neural Networks (RNNs) (Rumelhart et al., 1986) or Long Short-Term Memory (LSTM) NNs, and approaches based on Transformers and Sequence-to-Sequence Learning methodology due to their capabilities of solving sequence related prediction problems. Along with the annotations, we will apply a simpler approach to sentiment analysis as a basis for comparison with the NN solution. This classical method uses keywords expressing specific emotions. This approach was presented in a well-known article published in Science by (2011), where a list of keywords has been used to estimate the general mood of people. The measures show good validity, consistent with the effects of sleep and circadian rhythm (individuals awaken in a good mood that deteriorates as the day progresses). This approach is, however, a very general indicator of sentiments and has the limitation that the context cannot be taken into account, for instance, the presence of irony.

4.2.3 Facebook Data

Facebook is the most popular social media platform. It might be treated as distinctive realms in which much of the human experience now resides and moreover empirical studies shows that the structure of Facebook networks reflects the structure of real-life social networks (Dunbar et al., 2015). The FB data seems to be extremally attractive for researcher's data extraction does not rely on participants' (possibly biased) memory, and thus facilitates a more accurate measure of group density and size. Furthermore, FB are rich in content including: friend requests (sent and received; friend requests accepted (requests to others and requests from others); sharing content of different types (e.g., web links, photos, etc.); commenting on friends' content (receiving and giving); "liked" friends' content (receiving and giving); private messages (sent and received); tagging in photographs (tagging others and being tagged); group participation (joining, joining others to a group, being added by others); hiding friends on the news feed; accessing the site (on a computer, mobile device, etc.) and friend count. We will explore those data in context of network analysis, misinformation and polarization of opinions by tracking the diffusion of news (posts) in context of classical social network analysis focusing on structural cohesion or density of the group (Hanneman & Riddle, 2005). We will also investigate to what extent FB creates or accentuates an informational filter around individuals such that people only see ideologically compatible content (Bakshy et al., 2015).

Unlike Twitter, data from Facebook are not generally available for research purposes, but at least two strategies of obtaining data are possible. In this study the main mode of collecting Facebook data will be by inviting participants who allow to share their FB data for the purpose of research into the lab. Invited participants will login into their Facebook account and share their data. Reedy made tools like NetGet (Rieder, 2013) could be utilized to extract participants' Facebook data. The application requires participants to log on to their Facebook accounts, and allows for extraction of Facebook friend names and connections between them, as well as friends' genders, age ranks and wall post counts etc. The other way that will be explored is to prepare add-on applications on FB site and collect data online. When users opt in for such application it allows researchers access to users' demographic and behavioral data. and will be explored during the panel research. This however might be problematic in terms of changes that rapidly comes to FB platform and the data policies. Therefore, success of this approach might not be guaranteed and in this proposal, it will be explored as additional possibility.

This component is a high risk but high gain one. It is riskier than component 1 because we are proposing a novel methodology of measurement. However, the gain is high - providing new methodology that might be adopted also by other researchers and disciplines. Once again, we believe that the successful track of records of PI that showed the project could be successful. To facilitate the work on this part of the study we will set up a panel of experts that will advise the project and monitor the progress in yearly meetings in the form of a small seminar. For these seminars, we will invite world-class researchers that could share their knowledge and help to achieve the goals of the project.

4.3 Component 3: Applications for key social challenges

From the substantial perspective we will focus on five outcomes: (1) generalized trust, (2) political efficacy, (3) general health, (4) attitudes towards migrants, and (5) attitudes towards climate change and to contextual research topics (a) misinformation and (b) polarization of attitudes.

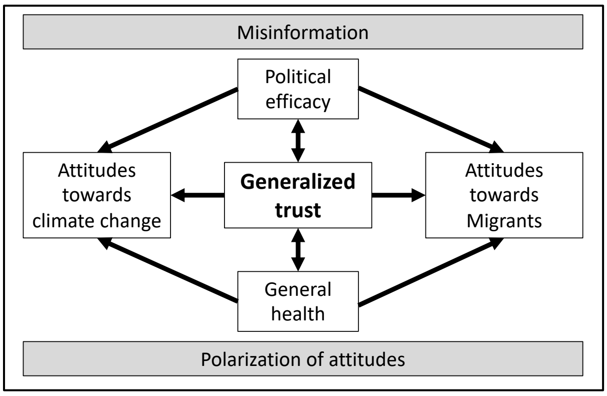

Figure 1. Map of investigated outcomes

The conceptual map of the investigation is presented in Figure 2. We do not want to focus on the **COVID-19** pandemic in this project (many other projects deal with this problem). Of course, we will not escape this because pandemic is stretching societal mechanism in terms of trust, political efficacy and of course health status. We hope that once the project will be running the COVID pandemic will constitute importing background, one of the mechanisms affecting variables and frame of reference but will not be the central point of future life. However, we believe that the project could provide additional value and complementary information on people's attitudes, behavior, knowledge, and health, information that is useful in understanding social responses to pandemic and policy measures and in helping policymakers to make more informed decisions and be more prepared for future shocks.

The generalized trust will play a central role in the analysis. **Generalized trust** corresponds to an "indiscriminate belief in the general benevolence of one's fellow citizen" (Sturgis et al., 2010) and reflects the "expectation that other members of the community will behave in a cooperative and honest way"(Fukuyama, 1995). To trust others is to believe that strangers will not knowingly hurt us and will consider our well-being when acting (Barber, 1983; Hardin, 2006). Generalized trust expresses confidence in the benevolent behavior of others (Delhey et al., 2011). Trust is an expression as well as a determinant of the quality of social interactions (Borgonovi & Pokropek, 2016). It characterizes social dynamics between an individual at the giving end of the trust relationship (the person who trusts) and an individual at the receiving end of such a relationship (the person who is trusted). The trust is an important indicator for modern societies. In societies with high levels of generalized trust individuals share new ideas and exchange information efficiently, and interact with each other to overcome collective action problems (Fukuyama, 1995; Ostrom, 2003; Putnam, 1993; Tavits, 2006). Empirical work confirms that generalized trust is an important social and economic resource: it is associated with economic development, functioning democratic institutions (Algan & Cahuc, 2010; Inglehart, 1997; Putnam, 1993) and political efficacy which is our second outcome variable (M. R. Anderson, 2010). Moreover, interpersonal trust provides sources of social and psychosocial support by establishing networks on which individuals can rely in times of need and by so doing may foster individual well-being (Kawachi & Berkman, 2001).

Political efficacy is considered as one of the most important factors that sustain and develop successful democratic systems (Almond & Verba, 1963; Pateman, 1970). Political efficacy is defined as 'the feeling that individual political action does have, or can have, an impact on the political process, i.e., that it is worthwhile to perform one's civic duties' (Campbell et al., 1954). Political efficacy is closely associated with political participation and can be considered a building block of political trust (Valentino et al., 2009).

Generalized trust is known to be positively associated with **health status** (Islam et al., 2006; Rocco et al., 2014), the third outcome in our analysis. Interpersonal trust may promote better health by decreasing transaction costs, increasing access to material resources and to health-related information as well as promoting the development of informal insurance arrangements (Stephens-Davidowitz & Pabon, 2017; Viswanath et al., 2006). When individuals trust anonymous others, it is easier to reach a consensus out of different group interests, thus allowing for more efficient interactions (Ostrom, 2003; Putnam, 1993; Tavits, 2006). Poor health is a major burden for the affected individual, but also for governments. Recent estimates suggest that health expenditures account for as much as 9% of GDP across OECD countries; in the United States, they represent as much as 16% of GDP (Indicators, 2005). In our study, we will predict the general health status in surveys using self-reports ("How is your health these days?"). Self-reported health is an important predictor of mortality and of the onset of disability and stress levels (Farmer & Ferraro, 1997). Self-reported health measures have high levels of validity and consistency (Weziak-Bialowolska, 2014).

As indicated earlier relation between trust, political efficacy and health are well documented, however, as mentioned above, empirical evidence on the direction of the relationships is limited. We expect that additional evidence from this project will provide additional insights to this issue. Moreover, we want to investigate two additional variables, especially important from the political and scientific perspectives: attitudes towards migrants and climate change.

An estimated 4.9 million **migrants** arrived in the European countries in 2015 (EUROSTAT, 2018) and while this figure was part of a long and steady upward trend in the share of foreign-born populations residing in European countries, 2015 figures represented a sudden and sizable increase of over the 4 millions of arrivals registered in 2014 (EUROSTAT, 2018). Migration flows, particularly sudden increases in the number of new arrivals, can and did create difficulties for host communities. However, they also represent an opportunity for countries that face aging native-born populations and the associated threat of labor and skills shortages (OECD, 2018). The ability of societies to withstand the pressures on social cohesion posed by migration flows depends on the long-term integration of immigrants, which reflects the host community's capacity to facilitate the settlement of new arrivals as well as immigrants' own capacity to adapt and become part of both labor markets and social networks in countries of destinations. Attitudes towards migrants are of crucial importance for hosting societies but there is still some missing knowledge about mechanisms that shape attitudes towards migrants. Little is known about relations between attitudes towards migrants and social trust. On the one hand, conflict theories (Bach & Schraml, 1982) have hypothesized that exposure to ethnic diversity leads people to withdraw from the social life to the extent that they trust others less. On the other hand, contact theory (Pettigrew, 1998) postulates that people living in ethnically diverse contexts have more contact with immigrants which, in turn, increases trust and improves intergroup relations. Empirical results show that generalized trust is negatively related to anti-immigrant sentiments, however the relation is very weak and observed on cross-sectional data (van der Linden et al., 2017). Evidence on the relations between political efficacy and attitudes to the migration is also very limited. Are anti-immigration attitudes works as catalysator for political efficacy or just the opposite (Morales & Giugni, 2016)? Similarly, little is known about relation between general health and anti-migrant sentiments. Once again two theories (conflict vs. contact) suggest contrary predictions. For people with bad general health, migrants could been seen as a source of help or as an additional source of competition over social and economic resources (Olzak, 1992).

Another outcome **is attitudes toward climate change** or climate change awareness. Despite the well-established scientific knowledge about the effects of human activities on climate change, public opinion about climate change and the need for political actions related to global warming is very polarized (Aasen, 2017; Antonio & Brulle, 2011; Zhou, 2016). One of the biggest problems of modern civilization is far from reaching a reasonable solution. The problem requires a collective and coordinated response that is strictly related to consensus in attitudes toward climate change that are aimed to be monitored by detailed longitudinal data based on the methodology proposed in this project. Dense longitudinal data would allow examining how attitudes towards climate change are related to political actions (e.g. protests), natural events (e.g. heat waves) and media publication on related topics. Moreover, we want to relate attitudes towards climate change to trust, political efficacy and general health. There is growing literature about the interrelations between those variables. It seems that generalized trust shape attitudes toward climate change and pro-active environment behaviors (Kaltenborn et al., 2017), while political efficacy is directly related to attitudes towards climate change and might be an important factor for various sources of information that affects climate change awareness (Feldman et al., 2017). However, the evidence is limited and mostly based on cross-sectional data, disregarding temporal dimension. Finally, multiple sources report the impact of climate change on health (Cannon & Perry, 2017), however there is no strong evidence that decreasing health contribute to the climate change (or other environmental issues like air pollution) and therefore result in more climate change awareness.

Those outcomes will be analyzed in the context of fake news and misinformation. Because of social media development, every internet user become a broadcaster. The average Twitter user has 707 followers (Smith, 2019) to whom information can be delivered with almost no cost and in no time. The question asked in the proposal might be phrased: What is the dynamic course of consuming, sharing, and distributing mis/disinformation (e.g., fake news, conspiracy theories, mis/disinformation) and what is the causal direction between consuming misinformation and analyzed variables? Prior research suggests that FB users because of news feed algorithms receive ideologically compatible content (Bakshy et al., 2015). Algorithms of social media favors information that fits the user's profile of preferences and withholds information that does not. This results in so called echo chambers that reinforces the user's world view, leaving users confident that their own views and ideologies (Schwarz & Jalbert, 2020). Moreover it was shown that social media could alter perception of social ties (Eslami et al., 2015), and perceived social capital (Chung et al., 2012) altering the values, attitudes and opinions (that is the variable under our investigation). The high resolution of big data with its high context information will allow monitoring variation in those outcomes both on the regional level and across time and explain the relation with different angles.

5. Justification for appointing a new research team

Digital and computational sociology is relatively new field. The field is emerging with problems because it requires advanced technical knowledge to collect, manipulate and analyze big data. Those skills are not being thought in in social science departments. As the consequences the first wave of studies of online behavior has been dominated by computer scientists who seldom lack theoretical and methodological knowledge resulting in doubtful assumptions and meaningless detached from theory results. We believe that social sciences and sociology in particular should develop means for analyzing such relevant for social theory data. Up to our knowledge Poland lacks strong (or at least visible) social science teams that would push the field forward. Up to today only some individual exceptions (Jemielniak, 2019) are exploring the possibilities laying in big data. Regardless individual successes the field needs long-run solutions to adapt to the era of big data. This project is an attempt of building a unique teem whose task will be to advance digital data and advance methods to use online trace data together with survey data and contribute to solving current social problems.

6. Ethical dilemmas

Digital trace data raise challenging ethical and legal questions on how to protect individual privacy. The more detailed considerations are beyond the scope of this proposal. Here we just want to emphasize that all ethical questions will be examined carefully during the course of the project and special care and meticulousness will be applied to actions. The grant proposal, including information on data collection, will be presented and discussed with the local Ethical Committee. Only after approval of the Ethical Committee research action will take place.

7. Literature

Aasen, M. (2017). The polarization of public concern about climate change in Norway. In *Climate Policy* (Vol. 17, Issue 2, pp. 213–230).

Achrekar, H., Gandhe, A., Lazarus, R., Yu, S.-H., & Liu, B. (2011). Predicting flu trends using twitter data. *2011 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, 702–707.

Algan, Y., & Cahuc, P. (2010). Inherited trust and growth. In *American Economic Review* (Vol. 100, Issue 5, pp. 2060–2092).

Almond, G., & Verba, S. (1963). *The civic culture: Political attitudes and democracy in five nations*. Princeton, NJ: Princeton University Press.

Anderson, C. (2008). The end of theory: The data deluge makes the scientific method obsolete. In *Wired magazine* (Vol. 16, Issue 7, pp. 16–07).

Anderson, M. R. (2010). Community psychology, political efficacy, and trust. In *Political Psychology* (Vol. 31, Issue 1, pp. 59–84).

Aronson, E., Carlsmith, J. M., & Ellsworth, P. C. (1990). *Methods of research in social psychology*. McGraw-Hill New York.

Bach, R. L., & Schraml, L. A. (1982). Migration, crisis and theoretical conflict. In *International Migration Review* (Vol. 16, Issue 2, pp. 320–341).

Bakker, K. M., Martinez-Bakker, M. E., Helm, B., & Stevenson, T. J. (2016). Digital epidemiology reveals global childhood disease seasonality and the effects of immunization. In *Proceedings of the National Academy of Sciences* (Vol. 113, Issue 24, pp. 6689–6694).

Bakshy, E., Messing, S., & Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science*, *348*(6239), 1130–1132.

Barber, B. (1983). *The logic and limits of trust*.

Bauman, Z. (2013). *Consuming life*. John Wiley & Sons.

Baumgartner, H., & Steenkamp, J.-B. E. (2001). Response styles in marketing research: A cross-national investigation. In *Journal of marketing research* (Vol. 38, Issue 2, pp. 143–156).

Betsch, C., Wieler, L., Bosnjak, M., Ramharter, M., Stollorz, V., & Omer, S. (2020). COVID-19 Snapshot MOnitoring (COSMO): Monitoring knowledge, risk perceptions, preventive behaviours, and public trust in the current coronavirus outbreak. *Psych Archives*.

Borgonovi, F., & Pokropek, A. (2016). Education and Self-Reported Health: Evidence from 23 Countries on the Role of Years of Schooling, Cognitive Skills and Social Capital. *PloS One*, *11*(2), e0149716.

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Guilford publications.

Campbell, A., Gurin, G., & Miller, W. E. (1954). *The voter decides*.

Cannon, P., & Perry, M. (2017). *Climate Change and Mental Health: A Systematic Review*.

Chen, J. K. T., Valliant, R. L., & Elliott, M. R. (2019). Calibrating non-probability surveys to estimated control totals using LASSO, with an application to political polling. In *Journal of the Royal Statistical*

Society: Series C (Applied Statistics) (Vol. 68, Issue 3, pp. 657–681). https://doi.org/10.1111/rssc.12327

Chunara, R., Aman, S., Smolinski, M., & Brownstein, J. S. (2013). Flu near you: An online self-reported influenza surveillance system in the USA. In *Online Journal of Public Health Informatics* (Vol. 5, 1).

Chung, C. J., Nam, Y., & Stefanone, M. A. (2012). Exploring online news credibility: The relative influence of traditional and technological factors. *Journal of Computer-Mediated Communication*, *17*(2), 171–186.

Cizek, G. J. (2012). The forms and functions of evaluations in the standard setting process. In *Setting performance standards: Foundations, methods, and innovations* (pp. 165–178).

Cook, S., Conrad, C., Fowlkes, A. L., & Mohebbi, M. H. (2011). Assessing Google flu trends performance in the United States during the 2009 influenza virus A (H1N1) pandemic. In *PloS one* (Vol. 6, Issue 8, p. e23610).

Davies, G. (2018). *Examination of approaches to calibration in survey sampling* [Thesis]. http://orca.cf.ac.uk/id/eprint/109727

Delhey, J., Newton, K., & Welzel, C. (2011). How general is trust in "most people"? Solving the radius of trust problem. In *American Sociological Review* (Vol. 76, Issue 5, pp. 786–807).

Diakopoulos, N. A., & Shamma, D. A. (2010). Characterizing debate performance via aggregated twitter sentiment. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1195–1198.

Dunbar, R. I., Arnaboldi, V., Conti, M., & Passarella, A. (2015). The structure of online social networks mirrors those in the offline world. *Social Networks*, *43*, 39–47.

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., Hamilton, K., & Sandvig, C. (2015). *' I always assumed that I wasn't really that close to [her]' Reasoning about Invisible Algorithms in News Feeds*. 153–162.

Ettredge, M., Gerdes, J., & Karuga, G. (2005). Using web-based search data to predict macroeconomic statistics. In *Communications of the ACM* (Vol. 48, Issue 11, pp. 87–92).

Eysenck, S., Eysenck, H., & Shaw, L. (1974). The modification of personality and lie scale scores by special 'honesty'instructions. In *British Journal of Social and Clinical Psychology* (Vol. 13, Issue 1, pp. 41–50).

Farmer, M. M., & Ferraro, K. F. (1997). Distress and perceived health: Mechanisms of health decline. In *Journal of Health and Social behavior* (pp. 298–311).

Feldman, L., Hart, P. S., Leiserowitz, A., Maibach, E., & Roser-Renouf, C. (2017). Do hostile media perceptions lead to action? The role of hostile media perceptions, political efficacy, and ideology in predicting climate change activism. In *Communication Research* (Vol. 44, Issue 8, pp. 1099–1124).

Fisher, R. J. (1993). Social desirability bias and the validity of indirect questioning. In *Journal of consumer research* (Vol. 20, Issue 2, pp. 303–315).

Fisher, R. J., & Katz, J. E. (2000). Social-desirability bias and the validity of self-reported values. In *Psychology & marketing* (Vol. 17, Issue 2, pp. 105–120).

Fuchs, C. (2017). *Social media: A critical introduction*. Sage.

Fukuyama, F. (1995). *Trust: The social virtues and the creation of prosperity* (Vol. 99). Free press New York.

Gelman, A., & Carlin, J. (2002). Poststratification and Weighting Adjustments. In *Survey nonresponse*. Wiley.

Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, *333*(6051), 1878–1881.

Golder, S. A., & Macy, M. W. (2014). Digital footprints: Opportunities and challenges for online social research. *Annual Review of Sociology*, *40*, 129–152.

Graham, J. W., Taylor, B. J., & Cumsille, P. E. (2001). *Planned missing-data designs in analysis of change*.

Hanna, A., Wells, C., Maurer, P., Friedland, L., Shah, D., & Matthes, J. (2013). Partisan alignments and political polarization online: A computational approach to understanding the French and US presidential elections. *Proceedings of the 2nd Workshop on Politics, Elections and Data*, 15–22.

Hanneman, R. A., & Riddle, M. (2005). *Introduction to social network methods*. University of California Riverside.

Harari, Y. N. (2016). *Homo Deus: A brief history of tomorrow*. Penguin Random House Group Ltd.

Hardin, R. (2006). *Trust. Cambridge: Polity*.

Heaivilin, N., Gerbert, B., Page, J. E., & Gibbs, J. L. (2011). Public health surveillance of dental pain via Twitter. *Journal of Dental Research*, *90*(9), 1047–1051.

Hynes, M. (2018). Shining a brighter light into the digital 'black box': A call for stronger sociological (re) engagement with digital technology design, development and adoption debates. In *Irish Journal of Sociology* (Vol. 26, Issue 1, pp. 94–126).

Inglehart, R. (1997). *Modernization and postmodernization: Cultural, economic, and political change in 43 societies* (Vol. 19). Cambridge Univ Press. http://journals.cambridge.org/production/action/cjoGetFulltext?fulltextid=6296904

International Telecommunication Union. (2019). *Measuring digital development Facts and figures 2019*. International Telecommunication Union. https://www.itu.int/en/ITU-D/Statistics/Documents/facts/FactsFigures2019.pdf

Islam, M. K., Merlo, J., Kawachi, I., Lindström, M., & Gerdtham, U.-G. (2006). Social capital and health: Does egalitarianism matter? A literature review. In *International journal for equity in health* (Vol. 5, Issue 1, p. 3).

Java, A., Song, X., Finin, T., & Tseng, B. (2007). Why we twitter: An analysis of a microblogging community. *International Workshop on Social Network Mining and Analysis*, 118–138.

Jemielniak, D. (2019). *Socjologia internetu*. Wydawnictwo Naukowe Scholar Sp. z oo.

Jinasena, S. (2014). Social Media Impact on Youth Depression. In *Sociology and Anthropology* (Vol. 2, Issue 7, pp. 291–294).

Jungherr, A. (2016). Twitter use in election campaigns: A systematic literature review. *Journal of Information Technology & Politics*, *13*(1), 72–91.

Jungherr, A., Jürgens, P., & Schoen, H. (2012). Why the pirate party won the german election of 2009 or the trouble with predictions: A response to tumasjan, a., sprenger, to, sander, pg, & welpe, im "predicting elections with twitter: What 140 characters reveal about political sentiment". *Social Science Computer Review*, *30*(2), 229–234.

Kaltenborn, B. P., Krange, O., & Tangeland, T. (2017). Cultural resources and public trust shape attitudes toward climate change and preferred futures—A case study among the Norwegian public. In *Futures* (Vol. 89, pp. 1–13).

Kawachi, I., & Berkman, L. F. (2001). Social ties and mental health. In *Journal of Urban health* (Vol. 78, Issue 3, pp. 458–467).

Khorramdel, L., & von Davier, M. (2014). Measuring response styles across the Big Five: A multiscale extension of an approach using multinomial processing trees. In *Multivariate Behavioral Research* (Vol. 49, Issue 2, pp. 161–177).

Kitchin, R. (2014). Big Data, new epistemologies and paradigm shifts. In *Big data & society* (Vol. 1, Issue 1, p. 2053951714528481).

Kuhn, T. S. (1962). *The structure of scientific revolutions*. University of Chicago press.

Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google Flu: Traps in big data analysis. In *Science* (Vol. 343, Issue 6176, pp. 1203–1205).

Lilleberg, J., Zhu, Y., & Zhang, Y. (2015). Support vector machines and word2vec for text classification with semantic features. In *2015 IEEE 14th International Conference on Cognitive Informatics & Cognitive Computing (ICCI* CC)* (pp. 136–140). IEEE.

Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.

McCormick, T. H., Lee, H., Cesare, N., Shojaie, A., & Spiro, E. S. (2017). Using Twitter for Demographic and Social Science Research: Tools for Data Collection and Processing. *Sociological Methods & Research*, *46*(3), 390–421. https://doi.org/10.1177/0049124115605339

Morales, L., & Giugni, M. (2016). *Social capital, political participation and migration in Europe: Making multicultural democracy work?* Springer.

Mytton, G., Diem, P., & Van Dam, P. H. (2016). *Media Audience Research: A guide for professionals*. SAGE Publications India.

Nadella, S. (2017). *Build 2017*. Build Conference 2017, Seattle,. https://news.microsoft.com/uploads/2017/05/Build-2017-Satya-Nadella-transcript.pdf

Newman, M. W., Lauterbach, D., Munson, S. A., Resnick, P., & Morris, M. E. (2011). *It's not that i don't have problems, i'm just not putting them on facebook: Challenges and opportunities in using online social networks for health*. 341–350.

OECD. (2018). *International migration outlook*. OECD publishing.

Ofcom. (2015). *Adults Media Use and Attitudes*. https://www.ofcom.org.uk/researchand- data/media-literacy-research/adults-media-use-and-attitudes

Olzak, S. (1992). *The Dynamics of Ethnic Competition and Conflict*. Standford University Press.

Ostrom, E. (2003). Toward a behavioral theory linking trust, reciprocity, and reputation. In *Trust and reciprocity: Interdisciplinary lessons from experimental research* (Vol. 6, pp. 19–79).

Park, D. K., Gelman, A., & Bafumi, J. (2004). Bayesian multilevel estimation with poststratification: State-level estimates from national polls. In *Political Analysis* (Vol. 12, Issue 4, pp. 375–385).

Pateman, C. (1970). *Participation and democratic theory*. Cambridge University Press.

Paulhus, D. L., Harms, P. D., Bruce, M. N., & Lysy, D. C. (2003). The over-claiming technique: Measuring self-enhancement independent of ability. In *Journal of personality and social psychology* (Vol. 84, I. 4).

Pettigrew, T. F. (1998). Intergroup contact theory. In *Annual review of psychology* (Vol. 49, 1, pp. 65–85).

Phillips, D. L., & Clancy, K. J. (1972). Some effects of" social desirability" in survey studies. In *American Journal of Sociology* (Vol. 77, Issue 5, pp. 921–940).
Pokropek, A. (2011). Missing by design: Planned missing-data designs in social science. *ASK. Research & Methods*, *20*, 81–105.
Pokropek, A., Davidov, E., & Schmidt, P. (2019). A monte carlo simulation study to assess the appropriateness of traditional and newer approaches to test for measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, *26*(5), 724–744.
Prensky, M. (2009). H. sapiens digital: From digital immigrants and digital natives to digital wisdom. In *Innovate: Journal of online education* (Vol. 5, Issue 3, p. 1).
Putnam, R. (1993). The prosperous community: Social capital and public life. In *The american prospect* (Vol. 13, Issue Spring), Vol. 4. Available online: http://www. prospect. org/print/vol/13 (7 April 2003).
Reips, U.-D., & Garaizar, P. (2011). Mining twitter: A source for psychological wisdom of the crowds. *Behavior Research Methods*, *43*(3), 635.
Rieder, B. (2013). Studying Facebook via data extraction: The Netvizz application. *Proceedings of the 5th Annual ACM Web Science Conference*, 346–355.
Rocco, L., Fumagalli, E., & Suhrcke, M. (2014). From social capital to health–and back. In *Health economics* (Vol. 23, Issue 5, pp. 586–605).
Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, *323*(6088), 533–536.
Salganik, M. (2019). *Bit by bit: Social research in the digital age*. Princeton University Press.
Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, *61*, 85–117.
Schmidt, E. (2017). *Alphabet's Eric Schmidt: We Should Embrace Machine Learning—Not Fear It* [Newsweek, January 10, 2017]. http://www.newsweek.com/2017/01/20/google-eric-schmidt-embrace-machine-learning-not-fear-it-540369.html
Schwarz, N., & Jalbert, M. (2020). WHEN (FAKE) NEWS FEELS TRUE. *The Psychology of Fake News: Accepting, Sharing, and Correcting Misinformation*.
Smith, K. (2019). Incredible and interesting Twitter stats and statistics. *Brandwatch*. https://www. brandwatch. com/blog/twitter-stats-and-statistics
Solano, P., Ustulin, M., Pizzorno, E., Vichi, M., Pompili, M., Serafini, G., & Amore, M. (2016). A Google-based approach for monitoring suicide risk. In *Psychiatry research* (Vol. 246, pp. 581–586).
Steadman, I. (2013). Big data and the death of the theorist. In *Wired Online* (Vol. 25, p. 2013).
Stephens-Davidowitz, S., & Pabon, A. (2017). *Everybody lies: Big data, new data, and what the internet can tell us about who we really are*. HarperCollins New York.
Sturgis, P., Read, S., Hatemi, P. K., Zhu, G., Trull, T., Wright, M. J., & Martin, N. G. (2010). A genetic basis for social trust? In *Political Behavior* (Vol. 32, Issue 2, pp. 205–230).
Tavits, M. (2006). Making democracy work more? Exploring the linkage between social capital and government performance. In *Political Research Quarterly* (Vol. 59, Issue 2, pp. 211–225).
Thompson. (2013). *Smarter than you think: How technology is changing our minds for the better*. Penguin.
Tsay-Vogel, M., Shanahan, J., & Signorielli, N. (2018). Social media cultivating perceptions of privacy: A 5-year analysis of privacy attitudes and self-disclosure behaviors among Facebook users. In *New media & society* (Vol. 20, Issue 1, pp. 141–161).
Valentino, N. A., Gregorowicz, K., & Groenendyk, E. W. (2009). Efficacy, emotions and the habit of participation. In *Political Behavior* (Vol. 31, Issue 3, p. 307).
van der Linden, M., Hooghe, M., de Vroome, T., & Van Laar, C. (2017). Extending trust to immigrants: Generalized trust, cross-group friendship and anti-immigrant sentiments in 21 European societies. In *PloS one* (Vol. 12, Issue 5).
Viswanath, K., Randolph Steele, W., & Finnegan Jr, J. R. (2006). Social capital and health: Civic engagement, community size, and recall of health messages. In *American Journal of Public Health* (Vol. 96, Issue 8, pp. 1456–1461).
Weziak-Bialowolska, D. (2014). Health conditions in regions of Eastern and Western Europe. In *International journal of public health* (Vol. 59, Issue 3, pp. 529–539).
Yardi, S., & Boyd, D. (2010). Dynamic debates: An analysis of group polarization over time on twitter. *Bulletin of Science, Technology & Society*, *30*(5), 316–327.
Zuboff, S. (2019). *The age of surveillance capitalism: The fight for a human future at the new frontier of power*. Profile Books.