Italian Sociological Review
University of Verona, Italy
ISSN 2239-8589 | Editor in Chief Paola Di Nicola
Managing Editor Debora Viviani

Epistemic Orientation for the Technological Future. Toward a Research Agenda for Dealing with Social Challenges of Internet of Things

Enrica Amaturo, Biagio Aragona, Cristiano Felaco

How to cite
Amaturo, E., Aragona, B., Felaco, C. (2022). Epistemic Orientation for the Technological Future. Toward a Research Agenda for Dealing with Social Challenges of Internet of Things. [Italian Sociological Review, 12 (7S), 635-649]
Retrieved from [http://dx.doi.org/10.13136/isr.v12i7s.574]

[DOI: 10.13136/isr.v12i7S.574]

1. Author information

Enrica Amaturo
Department of Social Sciences, University of Naples Federico II, Naples, Italy

Biagio Aragona
Department of Social Sciences, University of Naples Federico II, Naples, Italy

Cristiano Felaco
Department of Social Sciences, University of Naples Federico II, Naples, Italy

2. Author e-mail address

Enrica Amaturo
E-mail: amaturo@unina.it

Biagio Aragona
E-mail: aragona@unina.it

Cristiano Felaco
E-mail: cristiano.felaco@unina.it

3. Article accepted for publication

Date: May 2022

Epistemic Orientation for the Technological Future. Toward a Research Agenda for Dealing with Social Challenges of Internet of Things

Enrica Amaturo,[*] Biagio Aragona,[*] Cristiano Felaco[*]

Corresponding author:
Cristiano Felaco
E-mail: cristiano.felaco@unina.it

Abstract

This paper offers an epistemological and theoretical framework, and a research agenda, to face the main ethical and social pitfalls of the deployment of big data and IoT in social domains (SIoT). We rely on the concept of critical optimism to explain epistemic orientation about the technological future, paying particular attention to the social challenges. The framework drives the creation of an agenda for social researchers that aids to detect more evidence on the SIoT opportunities.

Keywords: critical optimism, digital epistemology, SIoT.

1. Introduction

The article aims at promoting an epistemological and theoretical framework for unfolding the increasing implementation of Social Internet of Thinghs (SIoT) in society, and at defining a social research agenda to tackle the social challenges of social IoT.

The expanding use of the IoT and social IoT is mainly in four social domains: Healthcare, Intelligent Transportation System, Smart Places (i.e., cities and homes) and Societal Interaction (Afzal et al., 2019, Vahdat-Nejad, Mazhar-Farimani, Tavakolifar, 2019). However, the collection, management, and analysis of massive data raise many ethical and societal issues. Security and privacy of the data concerns, as well as more substantial questions about the

[*] Department of Social Sciences, University of Naples Federico II, Naples, Italy.

influence and the control that these technologies can have on individuals' lives, have been underlined. If there is a risk that IOT may cause privacy breaches, or that may limit individual behaviours, this undermines citizens' feelings of trust in these technologies, and in the institutions and corporations that use them.

As a first consequence of such criticisms, the deployment of big data and IoT in society has been problematized, if not disapproved, by many social scientists in various research fields (Conte, 2016; Kitchin, Lauriault, 2015; Pasquale, 2015). Furthermore, problems of trust by citizens and customers have emerged, and these technologies are seen with an increasing suspect.

In order to tackle these challenges from a social perspective, rather than a technical one, we propose an epistemological posture, a theoretical framework, and a research agenda. In the first section, we present critical optimism, a concept that has served many authors to explain epistemic orientation about the technological future. Furthermore, in the second section, we propose a wide theoretical framework to mitigate the ethical and social pitfalls of the deployment of big data and IoT in social domains. Finally, in the third section, we draw an agenda for social researchers that could help to gain evidence about the great opportunities that SIoT may offer, but without dismissing their challenges.

2. The epistemology of big data and the Internet of Things: critical optimism

Big data and the Internet of Things (IoT) have generated two opposite epistemic positions in the scientific literature. On this controversy, we can draw a dividing line between those who are optimistic and those who are generally more critical (Salganik, 2018). Optimists argue that big data and IoT represented the new gold of the social sciences (Lazer et al., 2009; Mayer-Schönberger, Cukier, 2012); while critics feared that the spread of big data and IoT led to an impoverishment of the social sciences (Savage, Burrows, 2007). A kind of opposition that Amaturo and Aragona (2021) recalls the opposition between Apocalyptic and Integrated that Eco (1964) expressed to explain the different views about popular culture.

Two are the main debated topics around this diatribe: the data, and the technology. The optimists believe that more data equal better knowledge. This of course is not sustained by facts; consider, for example, how a large amount of data may increase the level of "noise" in data, so we can hardly distinguish rumors from signals (Torabi Asr, Taboada, 2019). Moreover, quantity does not mean necessarily high quality of data itself, because the risk of garbage in - garbage out is higher (Pasquale, 2015).

The same divergences also emerge concerning the role of technology. Similarly, optimists have faith in technology, it is seen as the driver of innovation and advances in knowledge. On the contrary, most critics believe that the reconfigurability of digital infrastructures and devices is contested and needs continued demonstration and testing (Marres, 2017). Big data and IoT are effective as far as we would be in the condition to inspect the theoretical assumptions and the socio-technical processes that shape them.

Despite these conflicting positions, a large group of scholars today supports an active commitment of social scientists in dealing with the technological dimension of knowledge (Daniels, Gregory, Mc Millan Cottom, 2016; Lupton, 2015; Orton-Johnson, Prior, 2013). This is an optimistic and, at the same time, critical position regarding the use of big data and IoT, better known as critical optimism (Amaturo, Aragona, 2021), a concept employed in several disciplines, from pedagogy (Freire, 1996) to art history and computer engineer (Brueckner, 2017), to explain orientation about the future.

According to this position, we advocate here that to effectively improve society, IoT and big data have to be integrated with traditional data sources and methods already existing in social sciences. This calls for a new epistemology of the social that is fully open to the possibilities offered by technology, but, at the same time, adopts a critical posture on the role that digital technology must play in society (Halford, Savage, 2017). This posture requires great attention to the epistemology of the digital, which refers not only to the evaluation of the limits of knowledge produced through data-intensive technologies, but also to the analysis of the short and long-term consequences that these technologies are having on the relationship between society and its representation in data, and on the relationship between these data and the social theories.

First of all, the separation between the phenomena and their representations is overcome because the use of distributed sensors, such as SIoT, is intersubjective, that is social reality is dependent on the sociotechnical activities that are made to grasp it. This conception acknowledges the role of platforms (Van Dijck, Poell, DeWaal, 2018) and «methodological dispositifs» (Ruppert, 2013) in shaping society, and, at the same time, considers that technology produces and is produced by society, being both social and material (Ruppert et al., 2013). The term "methodological dispositifs" is properly used to indicate this inextricable connection between technology and the social.

Furthermore, another issue concerns the relation between social theory and data. The neo-empiricism supports the idea that data speak for itself, without the need for intervening theory, and considers induction as the model to make inferences. According to Kitchin (2014), big data and IoT have changed the inference-making process by promoting a joint use of induction and deduction. In this angle, knowledge is pursued using "guided" computational techniques to discover hypotheses to be submitted to subsequent empirical control. The process is guided because the existing theories are used to direct the development of the discovery and not to identify all the existing relationships in a database. Instead, how data are constructed or re-analyzed is guided by some assumptions, supported by theoretical and practical knowledge and experience of how technologies and their configurations can produce valid and relevant empirical material. In practice, the method used is abductive (Peirce, 1883), also known as inference to the best explanation, which is the procedure of choosing the hypothesis or theory that best explains the available data (Harman, 1965).

Finally, critical optimism assumes an epistemology that takes into account the role of computational analytical methods in social research to produce new visions of social phenomena, without however excluding the constant testing of the methodological capacity of these tools. The use of big data and IoT must be openly discussed, evaluating the impacts on both science and society. The methodological reflection on the application of real-time analytics, along with the combination of big data sources and researcher-collected data leads to the production of more accurate and timely measures.

It is only in an abductive and critical posture that the current technological character of the unfolding of social phenomena through big data and IoT can be profitably reported within the different epistemological traditions of social sciences.

3. Big data is more than just data: a theoretical framework

The social IoT uses distributed sensors and other connected devices that have been said to improve social solutions, and sensors for collecting vast amounts of data are becoming an integral part of our societies and lives. There are at least three reasons for making this happen. First of all, timeliness; monitoring in real-time is the main change brought by IoT and big data and this is because sensors allow big data to be collected continuously (King, Pan, Roberts, 2013; Lorentzen, 2014). Furthermore, big data are fine-grained in their resolution, and their resolution has been accompanied by the identification of sensors and devices on the internet. This is a transformative innovation that helps to create continuous feedback within each stage of solutions planning and service delivery, rather than leaving feedback only to the final evaluation stage (Höchtl, Parycek, Schöllhammer, 2016).

The development, deployment, and increasing use of big data and IoT in society concern not only technology but also the socio-technical systems of which they are part, that is, the organizational and societal contexts in which these technologies are implemented. In order to figure out the role that Big Data and IoT may play in society, we suggest developing more theoretical thinking about some aspects which characterize Big Data (Aragona, De Rosa, 2019).

The first matter concerns the existing sources (traditional data, scaled-up Big Data, born-digital Big Data) and data infrastructures (data holding, data archives, repositories, etc.) that store, integrate, connect and disseminate data on a particular topic. Big data are not just data or only massive digital traces on the internet, but also data that operate in context alongside traditional forms of data. The main challenge for those who work with digital data is to be able to assess the reliability of the outcomes of an analysis (Rogers, 2013). A valid way of assessing an analysis obtained through internet data is an offline benchmark. According to the strand of critical data studies (Boyd, Crawford, 2012; Snijders, Matzat, Reips, 2012), Big Data and IoT may be properly addressed by combining different types of data. In this view, the attention should be moved from the 'Big Data revolution' to the 'all data revolution' (Lazer et al., 2014). By mixing surveys and process produced Big Data, Internet of Things, and administrative registers, the quality of both traditionally collected data and new digital data can improve. The examples of the use of IoT and big data for population and tourism mobility are emblematic. The use of location mobile phone's data for population and tourism statistics allows almost instantaneous population mobility analyses (De Jonge, Van Pelt, Roos, 2012) but does not allow to figure out why the people move (for example, leisure, work, etc.) or which means of transport prefer or use.

A further element to consider when reflecting on the consequences of the use of SIoT in society is the whole of actors, networks, roles, and systems of influence involved in the production and use of Big Data. In facing of growing complexity and multidimensionality of services' delivery and policy systems, it becomes essential to reconstruct the networks, roles, objectives, and power relationships of actors involved in the production and use of Big Data and IoT. In this light, focus groups and interviews are probably the techniques best suited to investigate the cultural aspects of technology, then the wider spectrum of values needs, visions embedded in it. The collaboration of relevant actors can play a crucial role in the effective employment of Big Data and IoT in different sectors. Data collaboratives between these actors may be seen as an emerging form of public-private partnership that produces a new public value (Verhulst, Young, 2017).

The final element of our theoretical framework for big data and IoT deployment in society is the repertoire of practices used to transform Big Data into actionable knowledge. The whole of practices must be assessed not in isolation, but jointly with technologies, devices, and infrastructures along with values, symbols, expert knowledge, disciplinary discourses, formal regulation, interests, and logics of action. It should be acknowledged that each actor contributes to the definition of a specific data culture, which shapes the connection between the moment when data are constructed and the moment when they are used to produce knowledge in a specific domain (Aragona, 2008; Sgritta, 1998). For example, by interviewing technicians, or conducting an ethnography of a Big Data team it can be uncovered the story behind the design of data and technology. This qualitative research has been firstly advocated by Science, Technology and Society (STS) studies (Latour, 1987), that inquiry how they framed objectives, designed decisions, and choices concerning languages and practices, influences, constraints, debates within a team or with stakeholders. STS studies allow focusing on how the centres of calculation – in which Big Data are assembled – are intended as heterogeneous assemblage where meanings and interests are negotiated within a socio-material network of entities. Critical data studies have been carried out to understand the assemblages more deeply through which Big Data are produced and the networks through which these are activated (Kitchin, Lauriault, 2017). These studies apply critical social theory to data to explore how they are never neutral, objective, raw representations of the world but are situated, contingent, relational and contextual. And they take advantage of mixed methods research designs, where quantitative analysis is integrated with qualitative studies using focus groups, interviews, and ethnographic observation.

A quite interesting example is the work that has been done on researching algorithms (Kitchin, 2017). In the past ten years, a growing number of scholars have started to focus critical attention on software code and computation in order to unpack the algorithms. Some concentrated on how algorithms are generated (Bucher, 2012; Geiger, 2014), others on how they worked within a specific domain such as security (Ansolabehere, Eitan, 2012) and finance (Pasquale, 2015). All these works just show that algorithms, as well as data, are not neutral, impartial expressions of knowledge. Far from being neutral in nature, algorithms construct and implement regimes of knowledge (Kushner, 2013) and their use has normative implications (Anderson, 2011).

Despite their conclusions are not fully embraceable, all these critical studies raise some relevant issues that we would like to push further by launching a research program that by using social research may give some answers and solutions to the main ethical and social problems connected with the deployment of big data and IoT in society.

4. Ethics, privacy, and trust in SIoT: a social agenda

Internet of Things describes the interconnection of different devices with ubiquitous accessibility and built-in intelligence. The Social Internet of Things addresses the establishment of social relationships among interacting objects. SIoT is used with real-life IoT devices to engage in some socialization activities of daily life. Things can establish, autonomously concerning human, social relationships with other objects (Khan et al., 2017).

Different applications involve the constant interaction among a variety of devices, that, in turn, socialize and collaborate to achieve some specific tasks. The result is an ecosystem that allows people and smart objects to interact within a social structure of relationships (Baskiyar, Meghanathan, 2005). Through the opportunities provided by hyper-connected environments, SIoT raises a host of relevant ethical and societal issues that should not be taken in isolation, but jointly considered (Afzal et al., 2019; Allhoff, Henschke, 2018). According to these criticisms, we believe that the social pitfalls of SIoT should be dealt with not only technically, but also through social research. We propose then a social research agenda able to tackle some of the issues arising.

Various features of IoT might cause ethical and societal problems (Van den Hoven, 2013). The ubiquity, the fact that devices are everywhere, makes always more difficult to give up using the artifacts because they are increasingly equipped with Internet-connected devices. The tendency to create more and more small, transparent, almost invisible devices, thus reducing the possibility of inspecting, auditing, controlling quality, and accounting procedures. Then, the growing difficulty to separate natural objects, artifacts, and beings as a consequence of the easy transformation from one category into another based on tags, advanced design, and absorption in new networks of artifacts. All of these interacting objects have an identity, and the management of these identities might cause serious problems of security and control. More connections entail more data produced and transferred with the risks of being maliciously used. Yet, interconnected objects have their incorporated intelligence and autonomy which makes them substitutes for social life. These objects could interfere spontaneously with human events, in unexpected ways for the users and/or the designers.

The main debate around SIoT is mostly on property, accessibility, control, accuracy and private use of information (Popescul, Georgescu, 2014), all issues that may take different forms according to the specific domains (Allhoff, Henschke, 2018).

IoT has gained much significance in the domain of medical and social care (Ali et al. 2021). The applications of Health-related internet of things (H-IoT) can monitor parameters such as heart rate, respiration, blood oxygen saturation, skin temperature, blood glucose, blood chemistry, and body weight that can be collected alongside behavioural parameters (i.e., motion, acceleration, mood) linked to health and well-being. These data are digitized, recorded, stored, and analyzed, creating novel opportunities for clinical care, by quickly informing specific treatments. For example, the smart medicine-box is a tool that interacts with the patients by interacting with body sensors to remind them of the dosage, and efficiently monitor and plan any change in it (Yang et al., 2014). Moreover, at-risk patients may benefit from H-IoT because they can be monitored for health emergencies or conditions, avoiding time-consuming activities such as home nursing observations (E-Health Insider, 2014). Despite these potentialities and the benefits, H-IoT raises a range of ethical problems stemming from the risks of Internet-enabled devices, the sensitivity of health-related data, and their impact on the delivery of healthcare (Mittelstadt, 2017). H-IoT devices generate a large volume and variety of data describing the personal health and behaviours of users. Much of these data can be used for medical research and patients' analytics. The design of protocols to enable user and third-party access to H-IoT datasets also raises ethical concerns.

How can H-SIoT innovation and its incredible potential be reconciled with the rigorous protection of individual guarantees and social rights? The legislation on artificial intelligence and automation is quite scattered worldwide, but some overarching principles are included in almost every piece of regulation, from the Canadian Directive on Automated Decision-Making to the EU's Ethics Guidelines for Trustworthy AI and Singapore's Model Artificial Intelligence Governance Framework, just to mention a few. These include transparency and accountability, freedom and control of humans, data protection, and risk management. Regarding data in the EU, for example, these kinds of rights are linked to Art. 22(3) of the EU GDPR, which rules that "the data controller shall implement suitable measures to safeguard the data subject's rights and freedoms and legitimate interests, at least the right to obtain human intervention". As Von der Leyen puts it: "We want to encourage our businesses, our researchers, the innovators, the entrepreneurs, to develop Artificial Intelligence. And we want to encourage our citizens to feel confident to use it" (European Union, 2020). While these regulations show the need to deal politically with the challenges that artificial intelligence poses, social research may help in unfolding these problems and building trust in these technologies.

The first point of our social research agenda is the involvement of the human actors that participate in the data assemblage SIoT through qualitative social research.

Torenholt and Langstrup (2021) carried out an ethnography to explore how medical sensors for clinical decision-making are enacted by healthcare professionals in Denmark. What the study showed is that the values through which these systems are promoted and sustained change between the different communities of stakeholders who are involved. While, at the health governance level, algorithms constitute tools for dismissing inefficient work, at the level of physicians, these tools represent everything but the disruption of their activities. Instead, they are legitimated as a continuation of standardized and systematic clinical activities for producing evidence-based diagnostic procedures that reinforce the physicians' expertise and authority. The authors conclude that between the two different communities of stakeholders, two divergent legitimation narratives are in place, but both provide a push toward the use of sensors in healthcare. Murero (2020) conducted an auto-ethnography (Anderson, 2006) of a health technological system to forecast cardiovascular disease in Berlin's hospitals. Ethnography enabled the author to observe technological design as the result of negotiations between multiple cultures, a heterogeneous ecosystem that competes and collaborates in complex infrastructure of practices, human and non-human (Seaver, 2013). For example, Murero shows how the expert communities reacted differently to the important issue of privacy that the management of a huge amount of sensitive health data had caused. While security experts pointed out the problem of asking for consent, computer scientists were concerned with anonymizing a large number of datasets coming from different devices. Physicians wanted instead to overcome all the troubles with the data to see if the system could really save lives. Access to the health data for training algorithms emerged as the result of a cooperative agreement of forces that required negotiation and authorization. The author concludes that the adoption of these systems in health is the final output of what she calls complex socio-tech-med cultures. Logics embodied in these systems are not only driven by data, devices, codes, and algorithms but are also regulated by human actions mediated by the cultural practices of specific communities of stakeholders. Much research about the social aspects of H-IoT deployment could gain knowledge about their ethical challenges.

Another example of SIoT is smart cities. They combine a host of data collection technologies and services to ensure cities are environmentally cleaner, safer, more productive, and more efficient (Kummitha, Crutzen, 2017; Neirotti et al., 2014). Utility providers may use many sensors and software systems to monitor and control the proper functioning of appliances located in private residences or buildings to efficiently distribute resources to allow for cost-effective services (Mohamed, Al-Jaroodi, Jawhar, 2018; Mosannenzadeh et. al., 2017). A further smart city application is Geographical Positioning Systems (GPS) tracking. The use of GPS devices relies on location information to operate effectively (Elmaghraby, Losavio, 2014), such as providing smart traffic light controls based on GPS information collected about the vehicles in a given area or giving emergency support by identifying the location of distressed residents (Clever et al., 2018). In these cases, smart cameras are employed to ensure greater safety, by detecting a dangerous situation in the street (theft, robbery, etc.), generating an alarm, and providing video footage to alert the mobile police vehicles.

These applications of SIoT have great potential but can be seen with the suspect by citizens because of the control all these sensors and devices may have on individuals' behaviour. The conjoint analysis of online traces, sensors, and the Internet of Things in urban contexts and smart cities is said to generate Big Brother effects in which the pervasiveness of technology becomes a tool for control. These criticisms have been fostered by the suspicions raised by journalists and whistleblowers about the use of algorithms to control citizens. Although we cannot fully agree with these criticisms, for SIoT to be really effective in the medium to long term, it is necessary to think about ways to foster trust. Social research can build evidence to address possible solutions. For example, some experiments can be run for understanding how these technologies work on a human value scale. A recent quasi-experiment was run by Ilinca Barsan (2021), director of data science at Wunderman Thompson, a marketing company that was developing a tool that would allow authorities to connect to thousands of street cameras and determine the proportion of pedestrians wearing masks at any given time. The computer vision APIs offered by Google, Microsoft, and IBM was intended to power the mask detection tool. However, they all exhibit gender bias when tested on self-portraits of people wearing partial face masks. If she would not run against this bias, and the tool for recognizing how many people in a streetwear mask would have been developed, it cannot be excluded that it would have then been employed by local governments to control the respect safety rules. Experimenting with the tools on ad hoc datasets constructed for the task may be the best research method to test for social biases and the reliability of the system. Image recognition is a really controversial example, that has been also coded in the Ethics Guidelines for Trustworthy AI where, when talking about face recognition, the document proposes a distinction between biometric "authentication", which is seen as non-controversial (e.g., face recognition to unlock a smartphone), and remote biometric "identification" (such as deployment in public squares to identify protesters), which could arouse serious human rights concerns. Only cases in the latter category would be problematic under the scheme proposed by the EU. One interesting example of building trust in technological systems for government solutions may be seen in what some consulting firms are trying to construct around data-intensive governance. With the city of Amsterdam, KPMG, together with the critical algorithm scholar Cathy O'Neil, are putting forward solutions to monitor smart city solutions and their performance by, on one side, detecting the ability to organize control of the adoption of such solutions effectively and, on the other side, analyzing the impacts that these systems have on citizens and organizations. These proactive control solutions, implemented by public and private partnerships under the surveillance of third-party bodies, which see an important role for researchers, can be the most effective ways to foster trust in automated decision-making systems. These solutions anticipate the risks of algorithmic governance and are more successful in building trust than what is simply referred to as transparency, which, without an effective audience, leads nowhere. Researching opinions and behaviour of the people impacted may be important to legitimate smart city solutions and is another way social research may help to tackle the challenges of SIoT, reducing distrust and mistrust in these technologies. For example, the application of surveys to data-intensive technologies is justified every time there is the objective of collecting opinions, attitudes, and behaviours of individuals impacted by data-intensive solutions in order to measure their level of acceptance. Running surveys about such themes allows public sector ICT to be examined not only from an economic and efficiency perspective but also a public value perspective, concerning its role in the production of social value. Positive and negative opinions can be useful for designing and readdressing public automating policies and for producing follow-up and evaluations that measure not only efficiency and spending but the social values that automation endorses.

References

Afzal, B., Umair, M., Shah, G.A., Ahmed, E. (2019), Enabling IoT platforms for social IoT applications: Vision, feature mapping, and challenges, *Future Generation Computer Systems*, 92, 718-731.

Ali, F., El-Sappagh, S., Islam, S.R., Ali, A., Attique M., Imran M., Kwak KS. (2021), An intelligent healthcare monitoring framework using wearable sensors and social networking data, *Future Generation Computer Systems*, 114, 23-43.

Allhoff, F., Henschke, A. (2018), The internet of things: Foundational ethical issues, *Internet of Things*, 1, 55-66.

Amaturo, E., Aragona, B. (2021), Critical Optimism: A Methodological Posture to Shape the Future of Digital Social Research, *Italian Sociological Review*, 11.

Anderson, C.W. (2011), Deliberative, agonistic, and algorithmic audiences: Journalism's vision of its public in an age of audience, *Journal of Communication*, 5, 529-547.

Anderson, L. (2006), Analytic autoethnography*, Journal of contemporary ethnography*, 35(4), 373-395.

Ansolabehere, S., Eitan, H. (2012), Validation: What Big Data Reveal About Survey Misreporting and the Real Electorate, *Political Analysis*, 20(4), 437-459.

Aragona, B. (2008), Una nuova cultura del dato, *Sociologia e Ricerca Sociale*, 87(3), 159-172.

Aragona, B., De Rosa, R. (2019), Big data in policy making, *Mathematical Population Studies*, 26(2), 107-113.

Barsan, I. (2021), Quantifying the accuracy of vision/facial recognition on identifying PPE masks. Available at https://www.wundermanthompson.com/insight/ai-and-gender-bias, (accessed 28 October 2021).

Baskiyar, S., Meghanathan, N. (2005), A Survey of Contemporary Real-time Operating Systems, *Informatica* (03505596), 29(2).

Boyd, D., Crawford, K. (2012), Critical questions for Big Data, *Information, Communication and Society*, 15(5), 662-679.

Brueckner, S. (2017), *Critical Optimism*, TEDxUofM.

Bucher, T. (2012), 'Want to be on the top?' Algorithmic power and the threat of invisibility on Facebook, *New Media and Society*, 14(7), 1164-1180.

Clever, S., Crago, T., Polka, A., Al-Jarood,i J., Mohamed, N. (2018), Ethical analyses of smart city applications, *Urban science*, 2(4), 96.

Conte, R. (2016), Big data: un'opportunità per le scienze sociali?, *Sociologia e ricerca sociale*, 18-27, 10.3280/SR2016-109003.

Daniels, J., Gregory, K., Mc Millan Cottom, T. (Eds.) (2016), *Digital sociologies*, Bristol, Policy Press.

De Jonge, E., Van Pelt, M., Roos, M. (2012), Time patterns, geospatial clustering and mobility statistics based on mobile phone network data. Discussion paper 201214, Statistics Netherlands. Available at: hiip://www.cbs.nl, (accessed 10 October 2021).

Eco, U. (1964), *Apocalittici e integrati*, Roma, Bompiani.

E-Health Insider. (2014). The year of the wearable. http://www.ehi.co.uk/insight/analysis/1404/the-year-of-the-wearable, 2014, (accessed 28 October, 2021).

Elmaghraby, A.S., Losavio, M.M. (2014), Cyber security challenges in Smart Cities: Safety, security and privacy. *Journal of Advanced Research*, 5, 491-497.

European Union, Press remarks by President von der Leyen on the Commission's new strategy: Shaping Europe's Digital Future. https://ec.europa.eu/commission/presscorner/detail/en/speech_20_294, 2020 (accessed 28 October 2021).

Freire, P. (1996), *Pedagogy of the oppressed*, New York, Continuum.

Geiger, R.S. (2014), Bots, bespoke, code and the materiality of software platforms, *Information, Communication & Society*, 17(3), 342-356.

Halford, S., Savage, M. (2017), Speaking sociologically with big data: Symphonic social science and the future for big data research, *Sociology*, LI(6), 1132-1148.

Harman, G.H. (1965), The inference to the best explanation, *The Philosophical Review*, 74.

Höchtl, J., Parycek, P., Schöllhammer, R. (2016), Big Data in the policy cycle: policy decision making in the digital era, *Journal of Organizational Computing and Electronic Commerce*, 26(1), 147-169. 10.1080/10919392.2015.1125187

Khan, W.Z., Aalsalem, M.Y., Khan, M.K., Arshad, Q. (2017), When social objects collaborate: Concepts, processing elements, attacks and challenges, *Computers & Electrical Engineering*, 58, 397-411.

King, G., Pan, J., Roberts, M.E. (2013), How censorship in China allows government criticism but silences collective expression, *American Political Review*, 107(2), 326–343.

Kitchin, R. (2014), *The Data Revolution: Big Data, Open Data, Data Infrastructures and Their Consequences*, London, Sage.

Kitchin, R. (2017), Thinking critically about and researching algorithms, *Information, Communication & Society*, 20(1), 14-29.

Kitchin, R., Lauriault, T.P. (2014), Towards critical data studies: Charting and unpacking data assemblages and their work, The programmable city working paper, 2.

Kitchin, R., Lauriault, T.P. (2015), Small data in the era of big data, *GeoJourna*l, 80(4), 463-476.

Kummitha, R.K.R., Crutzen, N. (2017), How do we understand smart cities? An evolutionary perspective, *Cities*, 67, 43-52.

Kushner, S. (2013), The freelance translation machine: Algorithmic culture and the invisible industry, *New Media & Society*, 15(8), 1241-1258.

Latour, B. (1987), *Science in action*, Cambridge, Harvard University Press.

Lazer, D., Brewer, D., Christakis, N., Fowler, J., King, G. (2009), Life in the network: The coming age of computational social science. *Science*, CCCXXIII, 5915, 721-723.

Lazer, D., Kennedy, R., King, G., Vespignani, A. (2014), Big data. The parable of Google Flu: traps in big data analysis, *Science*, 343(6176), 1203-1205.

Lorentzen, P. (2014), China's strategic censorship, *American Journal of Political Science*, 58(2), 402-414. doi:10.1111/ajps.2014.58.issue-2

Lupton, D. (2015), *Digital sociology*, London, Routledge.

Marres, N. (2017), *Digital sociology: The reinvention of social research*, New York, John Wiley & Sons.

Mayer-Schönberger, V., Cukier, K. (2012), *Big Data: A revolution that transforms how we work, live, and think*, Boston, Houghton Mifflin Harcourt.Mittelstadt, B. (2017), Ethics of the health-related internet of things: a narrative review, *Ethics and Information Technology*, 19(3), 157-175.

Mohamed, N., Al-Jaroodi, J., Jawhar, I. (2018), Service-Oriented Big Data Analytics for Improving Buildings Energy Management in Smart Cities. In Proceedings of the 14th International Conference on Wireless Communications and Mobile Computing (IWCMC), Limassol, Cyprus, 25-29 June 2018.

Mosannenzadeh, F., Bisello, A., Vaccaro, R., D'Alonzo, V., Hunter, G.W., Vettorato, D. (2017), Smart energy city development: A story told by urban planners, *Cities*, 64, 54-65.

Murero, M. (2020), Building artificial intelligence for digital health. A socio-tech-med approach, and a few surveillance nightmares, *Etnografia e ricerca qualitativa*, 13(3), 374-388.

Neirotti, P., De Marco, A., Cagliano, A.C., Mangano, G., Scorrano, F. (2014), Current trends in Smart City initiatives: Some stylised facts, *Cities*, 38, 25-36.

Orton-Johnson, K., Prior, N. (eds.) (2013), *Digital sociology: Critical perspectives*, Heidelberg, Springer.

Pasquale, F. (2015), *The black box society: The secret algorithms that control money and information*, Harvard, Harvard University Press.

Peirce, C.S. (ed.) (1883), *Studies in logic*, Boston, Little, Brown and Company.

Popescul, D., Georgescu M. (2014), Internet of Things–some ethical issues, *The USV Annals of Economics and Public Administration*, 13(2), 208-214.

Rogers, R. (2013), *Digital Methods*, Cambridge, MA MIT press.

Ruppert, E. (2013), Rethinking empirical social sciences, *Dialogues in Human Geography*, III(3), 268-273.

Ruppert, E., Law, J., Savage, M. (2013), Reassembling social science methods: The challenge of digital devices, *Theory, culture & society*, 30(4), 22-46.

Salganik, M.J. (2018), *Bit by bit: Social research in the digital age*, London, Princeton.

Savage, M., Burrows, R. (2007), The coming crisis of empirical sociology, *Sociology*, XLI, 5, 885-899, 10.1177/0038038507080443

Seaver, N. (2013), Knowing algorithms. Paper presented at Media in Transition 8, Cambridge, MA.

Sgritta, G.B., (ed.) (1998), *Immagini della società italiana*, Rome, ISTAT.

Snijders, C., Matzat, U., Reips, U. (2012), Big data: big gaps of knowledge in the field of internet science, *International Journal of Internet Science*, 7(1), 1-5.

Torabi Asr, F., Taboada, M. (2019), Big Data and quality data for fake news and misinformation detection, *Big Data & Society*, 6(1), 1-14.

Torenholt, R., Langstrup, H. (2021), Between a logic of disruption and a logic of continuation: Negotiating the legitimacy of algorithms used in automated clinical decision-making, *Health*, 1363459321996741.

Vahdat-Nejad, H., Mazhar-Farimani, Z., Tavakolifar, A., (2019), Social Internet of Things and New Generation Computing—A Survey, In A. E. Hassanien, R. Bhatnagar, N.E.M. Khalifa, M.H.N. Taha (eds.), *Toward Social Internet of*

Things (SIoT): Enabling Technologies, Architectures and Applications, pp. 139-149, Springer, Cham.

Van den Hoven, J. (2013), Internet of Things Factsheet Ethics, http://ec.europa.eu/digital-agenda/en/news/conclusions-internet-things-public-consultation (accessed at 28 October, 2021).

Van Dijck J., Poell T., DeWaal M. (2018), *The platform society: Public values in a connective world*, Oxford, Oxford University Press.

Verhulst, S.G., Young, A. (2017), The potential of social media intelligence to improve people's lives, Social Media Data for Good, The Governance Lab.

Yang, G., Xie, L., Mäntysalo, M., Zhou, X., Pang, Z., Da Xu, L., Kao-Walter, S., Chen, Q., Zheng, L. (2014), A health-iot platform based on the integration of intelligent packaging unobtrusive bio-sensor and intelligent medicine box, *IEEE Transactions on Industrial Informatics*, 10.4, 2180-2191.