Data Literacy in the Smart City: Why Smart Cities Should be Populated by MIL Citizens

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Abstract

Smart Cities typify the current and future data-rich environments. In these types of environments, technology and the analysis of vast data facilitate more intelligent choices and actions—largely automated using algorithms and artificial intelligence—related to mobility, security, energy use, culture, markets, etc. (Ballon, van der Graaf, & Walravens, 2017). A discussion on the necessity of data literacy has emerged from debates on datafication, big data, open data, artificial intelligence, and algorithms. The question, however, lies on the relation between media and data literacy. In this contribution, we reflect on aspects of data literacy by examining the literature on smart cities and data in smart cities. We argue that smart cities are not automatically media and information-literate cities. Furthermore, smart cities can only become media and information-literate cities by actively developing an open data context, involving citizens in data projects, empowering civil society participation, and stimulating data literacy in a broad sense.

Keywords: data literacy; Smart Cities; big data; digital turn; algorithms.

We live in an "age of data" (Bhargava et al., 2015), where everything surrounding us is linked to data sources, and our lives are captured digitally (Mojsilovic, 2018). "[T]he physical world around us has turned into raw information: Internet, video, call data records, customer transactions, healthcare records, news, literature, scientific publications, economic data, weather data, geo-spatial data, stock market data, city and government records" (Mojsilovic, 2018). A discussion has begun around the necessity of data literacy from debates on datafication, big data, open data, artificial intelligence, and algorithms This new discussion resonates with former debates on digital literacy during the digital turn and with current debates on algorithmic literacy (Oldridge, 2017), big data literacy (D'Ignazio & Bhargava, 2015), and coding literacy (Vee, 2017). We prefer the term "data literacy" because the data are the defining element in algorithms, artificial intelligence, deep learning, and platforms.
The "age of data" presents new challenges for media and information literacy scholarly community. On the one hand, some datafication processes are clearly situated in the field of media, such as search engines, recommendation engines, personalization of news, and the datafication of the user. On the other hand, some of these data-driven evolutions are situated in other fields, such as smart cities, smart environments, and data-based decision-making processes and policies. This evolution provides new opportunities but is also accompanied with possible risks, both within the media (such as filter bubbles and fake news) and in society(such as social sorting and digital exclusion mechanisms). Thus, the questions are as follows: what is the relation between media and data literacies? Are current models for media literacy sufficient to understand data literacy? What are their similarities and differences? How can we adapt existing models and frameworks to integrate data literacy?
In this contribution, we do not provide answers to all the questions. However, by considering the literature on smart cities and data in smart cities, we examine issues of data literacy. Precisely, why do we discuss data literacy in the smart city context? Should all citizens be data literate? In principle, the answer would be *yes*. However, some compelling arguments to consider on data literacy in the city context as follows:

1. Many medium- to large-sized cities are engaged in processes that encourage smart cities, which comprise technologies that result in time-sensitive, person-related, and location-based data that can be used by the city and its citizens. These data are gathered using sensors, tags, actuators, cameras, beacons, smartphones, wearables, and their associated apps, systems and applications (Ballon et al., 2017). These new technologies are referred to as *smart* because their use and the combination and analysis of all the data supposedly enables more intelligent choices and actions—both at the individual level (by citizens) and at the collective level (by companies and city governments)—related to mobility, security, energy use, culture, and markets at the city level (Ballon et al., 2017)

2. Cities harbor dense urban spaces that tend to generate denser and richer data than peri-urban and rural areas. Cities tend to contain more sophisticated infrastructures, sensors, and data points for data collection. Thus, it is logical that cities will be first movers in terms of digital and smart systems and processes.
3. Smart Cities and other cities are typically more engaged in open data projects, which provide citizens and intermediaries access to open datasets, allowing them to engage in data-driven policy preparation, advocacy, or protest.
4. Citizens might be more willing to engage politically—in the broad sense of the term—at the city level than at the national level.

In other words, smart cities make a good context to reflect on aspects of data literacy. Subsequently, we 1) map the current discussions on data literacy, 2) critically analyze the perceived goals of data literacy, 3) discuss three visions on the smart city, 4) examine the role of data in smart cities, 5) present a data literacy competence model, and 6) draw conclusions related to data literacy in the smart city.

Current Discussions on Data Literacy

The discussion on data literacy is only recent and certainly not as *mature* as those on media or information literacies. We should, therefore, be cautious of exaggerated reports of data literacy as promoted by certain think tanks and consultants. More so, the concept still remains unclear and has obvious associations with other *upcoming* literacies, such as algorithmic literacy (Oldridge, 2017), coding literacy (Vee, 2017), and big data literacy (D'Ignazio & Bhargava, 2015), as well as *established* literacies, such as numeracy and statistical literacies. We should carefully consider the boundaries of these types of literacies and their connection to media and information literacy. We begin by discussing the current definitions of data literacy. The Data-Pop Alliance defines data literacy as "the desire and ability to constructively engage in society through and about data (Bhargava et al., 2015)." This is a high-level definition that excels at indicating two basic components of data literacy: *using data* and *understanding data*. This is consistent with many definitions and competence models on media literacy (Van Audenhove et al., 2018). Numerous studies related to data literacy tend to focus on technical, computational, and statistical competences for working with datasets, referred to as *using data* (Gray et al., 2018). For instance, Prado & Marzel (2013) define data literacy as "(…) the component of information literacy that enables individuals to access, interpret, critically assess, manage, handle and ethically use data." Only a few studies have examined the role of data in society, the social construction of data, and the related biases. The Education Development Center defines that "The data literate individual understands, explains, and documents the utility and limitations of data by becoming a critical consumer of data, controlling his/her personal data (Oceans of Data Institute, 2016)." This definition, which initially lies between the concepts of *understanding data* and *using data*, proceeds to focus on competences for *using data:* "(He/she) can identify, collect, evaluate, analyze, interpret, present and protect data (Oceans of Data Institute, 2016)." Gray et al. (2018) focused on *understanding data* and proposed the concept of *data infrastructure literacy* "in order to both conceptualize and encourage critical inquiry, imagination, intervention and public experimentation around the infrastructures through which data is created, used and shared. Through this notion, we hope to suggest ways in which literacy initiatives might broaden their aspirations beyond data as an informational resource to be effectively utilized, by looking at how data infrastructures materially organize and instantiate relations between people, things, perspectives and technologies (Gray et al., 2018)." Knaus (2019), in a special data literacy issue of the *Journal of Media Literacy Education* argues similarly, calling for a critical media literacy in relation to data and technology, that moves beyond "(…) the 'outer shell' of machines—their interfaces—through to the technology itself and the data and algorithms which make it function" (Knaus, 2019).

The Goals of Data Literacy

In the literature, multiple reasons are provided for the need to invest in data literacy. In several works on open data, data literacy is regarded as a means of augmenting the impact of open data available to citizens (Boychuk et al., 2016; Frank & Walker, 2016), which is an instrumental view. Frank and Walker (2016), for instance, state that "(…) without data literacy, the impact of open data would be substantially reduced." These authors apparently question the feasibility of reaching sufficient levels of data literacy among the general population to engage with open data. The authors wonder whether *awareness by all* and *specific skills by experts* are the way forward (Frank & Walker, 2016). Others recommend that governments prepare datasets and translate data for citizen involvement (Boychuk et al., 2016). Wolf et al. (2017) opine that data literacy should be part of everyday thinking and reasoning for solving real-world problems. These problems can be tackled by using data as evidence, tool for innovation, and job opportunity. In terms of innovation, Wolf et al. (2017) specifically refer to open data and smart cities, stating that "in bottom-up smart cities, citizens are drivers for change, better placed for understanding their own local problems and proposing solutions that take citizens needs fully into account."

The current discussion is flawed by underlying assumptions that need further questioning, scrutiny, and tests. We briefly describe the assumptions in this section and address them further when discussing the role of data in the city context.

1. Several accounts on data literacy contain an inherent assumption that strengthening data skills and competences in terms of *using data* will automatically lead to a critical understanding of data as well as its role in different sectors and society (that is, *understanding data*). Similar views are held by some media-literacy authors (Van Audenhove et al., 2018). The idea is that *making media* leads to a better understanding of how media operate and its possible effects.
2. Numerous accounts on data literacy are premised on data being available, open, accessible, and free. In other words, data are available, and users with the skills to *read data, work with data, analyze data*, and *argue with data* (Bhargava et al., 2015) can exploit the data for personal gain or to change society politically.
3. Some accounts of data literacy reflect on the possible biases in datasets as well as in data collection and usage, or they consider possible risks of datafication, big data, and a data-driven society. These accounts apparently assume that citizens find it easy to recognize, uncover, and understand the biases and risks.
4. All accounts highlighted so far are based on a Western democratic philosophy, which relays that citizens can actively engage in civic processes in general and through and with data more specifically.

The Smart City

The smart city has multiple conceptualizations, and we begin by discussing two extreme perspectives before discussing a more integrated perspective. The first perspective is the technology-determined top-down approach. This perspective begins from the idea of a "control room" for the city, from which all urban activities are monitored and optimized (Hall, 2008). An Information and Communication Technologies (ICT)-based architecture in the city gathers vast amounts of data that form the basis of calculations, visualizations, and predictions (Campkin & Ross, 2013). This perspective has high economic prospects. Different services and infrastructure systems can be managed from one central hub that oversees several aspects of life in the city. Major IT companies (e.g., Cisco, IBM, Siemens) and municipalities around the world are exploring the possibilities of this approach (Townsend, 2013). Similar top-down visions have been criticized, the main argument being that they are driven by commercial interests while raising questions of control and privacy (Hollands, 2008; Kithchin & Dodge, 2011). Citizens are often unaware of the data gathered and the purpose for the gathering because decision-making processes based on these data are often untransparent for citizens and users of the systems.

The second perspective is the bottom-up approach. In this perspective, change and improvement proceed only from the people *using* the city. This perspective dismisses forms of top-down urbanization, particularly with the involvement of powerful private companies. The bottom-up smart city is, foremost, about the Smart Citizens: those who live, work, and engage in all kinds of activities in the city. Hence, rather than working toward centralization, this view adopts a distributed approach (De la Peña, 2013). While these characteristics have a positive impact on the local scale, they often conflict with the objectives of decision-makers, urban-planners, and the dynamics of the globalized economy. Chaotic bottom-up processes oppose the idea of a master plan: an "ideal" state of place. Here, the smart city is not defined by the infrastructures or architecture it offers but by the ways in which its citizens interact with these systems and with one other. However, relying solely on bottom-up initiatives remains problematic with regards to scalability, regulation, interoperability, barriers, and incentives to entry.

While both smart city perspectives have their merits, they are each flawed with certain characteristics: "Change seldom arises from purely top-down or bottom-up systems and processes" (Shepard & Simeti, 2013). A more integrated perspective is one that combines both top-down and bottom-up approaches: this perspective establishes the smart city as a platform that fosters a collective (local) intelligence of all affected stakeholders. After all, cities essentially constitute shared responsibility and resources (Campkin & Ross, 2013). Hence, we consider the smart city as a meeting place where the public sector, private interest, and citizens converge to generate new value, collaborate, and innovate, an idea that has also been referred to as the triple helix (private sector, government, and university actors) or quadruple helix (including citizens, the public, or the user, depending on the formulation) (Leydesdorff & Deakin, 2011). Smart Cities can only succeed if they act as local innovation platforms that bring together all involved stakeholders (Shepard & Simeti, 2013). The *government as a platform* (O'Reilly, 2011) is the intermediary: the enabler of multiple interactions among actors who have similar interests or needs. Public service delivery through such a reciprocal relationship between all stakeholders is a promising view for developing truly *smart cities* (Camponeschi, 2011). This type of collaboration also assumes a deep understanding of the data collected, used, interpreted, shared, and opened up for such an ecosystem to achieve sustainable results; this is where a more profound data literacy becomes important.

Data in the Smart City

An aspect deemed particularly important to "smarter" forms of governance is open data (Schaffers et al., 2011; Townsend, 2013). The idea is that governments possess a vast amount of information related to several aspects of life in the city, but these data are neither public nor easily interpretable. This has stirred a movement to encourage the opening of datasets in structured and machine-readable ways (under the "open data" coinage), which has gained significant attraction across local and national governments. The Open Knowledge Foundation is a strong proponent of this view and has come up with a generally accepted definition: "Open means anyone can freely access, use, modify and share for any purpose (subject, at most, to requirements that preserve provenance and openness)" (Open Knowledge Foundation, 2015). Thus, open data can be used for any goal at no cost with the exception that re-users credit the data source or do not in any way hinder the further sharing of the data.

In practice, however, a few challenges remain, and "merely" making data open has seldom proven successful (Lee et al., 2014; Peled, 2011). Making data open already poses considerable challenges for governments and public organizations before any data *leaves* the organization. Examples of these challenges include establishing internal processes to safeguard internal data hygiene, quality control, or implementation of new database systems or updating of existing ones. Relevant data can be distributed to different government organizations or levels of governance in different formats. This raises further challenges in combining the data into larger datasets for governments and citizens.

A substantial amount of data at the city level will most likely be gathered by private companies, as part of their own business within cities or as part of the tasks they execute for governments. Thus, some data may be under the control of private stakeholders who are generally less inclined to open the data up to the public. Höchtl et al. (2016) notes that data-driven policy making is prone to bias as most data-driven decision-making processes stem from industry, which has distinct needs and wants compared with the public sector. Therefore, there should always be a critical questioning of whether data-processing operations reflect the interests of the data owner and the public.

Vast amounts of data—even within public spaces—are automatically collected without the explicit consent of users. The big question is to what extent citizens are aware of data being gathered by automated processes at the city level. It is reasonable that automated data collection is more challenging for data literacy than consensual data collection. This is because automated data collection methods are less transparent and visible; thus, they are more difficult to grasp and understand by the population in general.

Data Literacy Competence Model

The smart cities discussions above demonstrate that the role of data in smart cities is highly complex, largely invisible, and, therefore, difficult to grasp. The role of data in society is not directly observable, neither at the level of data collection and processing, nor at the level of outcomes and impacts. In this sense, data literacy differs from media literacy. The outcome of the media is observable by the senses and directly visible or audible; the outcome of data is often not directly observable, and the data is inaccessible to citizens in numerous cases. Merely learning how to *use data* is insufficient to raise questions about who is collecting what data, for what use, and with what possible effects. This type of questions, knowledge, and the methods for uncovering data processes lie outside the spectrum of *using data* but reside within the humanities and social sciences fields while being less connected to the statistics, technology, and data science fields. Thus, we support the increased attention on data literacy but warn against current overemphasis on *using data*:

- the assumption that *using data* automatically leads to *understanding data* should be questioned and further investigated;
- the assumption that all citizens can and will acquire high levels of data literacy in terms of *using data* should also be questioned;
- it is reasonable to explore a more nuanced approach of viewing different levels of data literacy (who needs what levels of *data literacy* in terms of *using data* and *understanding data?*);
- we thus strongly argue for a competence framework that combines *using* and *understanding* data while placing them on an equal footing.

A similar model was recently developed by the Flemish Knowledge Centre for Media Literacy. The model comprises two major competence clusters: *using data* and *understanding data* (Mediawijs, 2020a). Competences refer to the knowledge, skills, and attitudes that allow individuals to act adequately in a given situation (Mediawijs, 2020b). The competence clusters are defined in more detail below.

- *Using data* (the knowledge, skills, and attitudes to use data actively and creatively)
  - interpreting: being able to read a graph, table, or list of data and understand what they mean;
  - navigating: finding one's way through a collection of data types and their processing methods while being able to extract the message of interest;
  - collecting: being able to establish a raw data collection process and organize a corresponding analysis; and

- presenting: being able to present and visualize the results of a well-targeted data analysis to a an audience.

- *Understanding data*: (the knowledge, skills, and attitudes to critically and consciously assess the role of data)
  - observing: being able to observe how data is communicated and used;
  - analyzing: being able to analyze the individual and social consequences of the way in which data is communicated and used;
  - evaluating: being able to evaluate whether those consequences are harmful or constructive; and
  - reflecting: being able to reflect on adjusting how you and others communicate and use data, to minimize the harmful consequences.

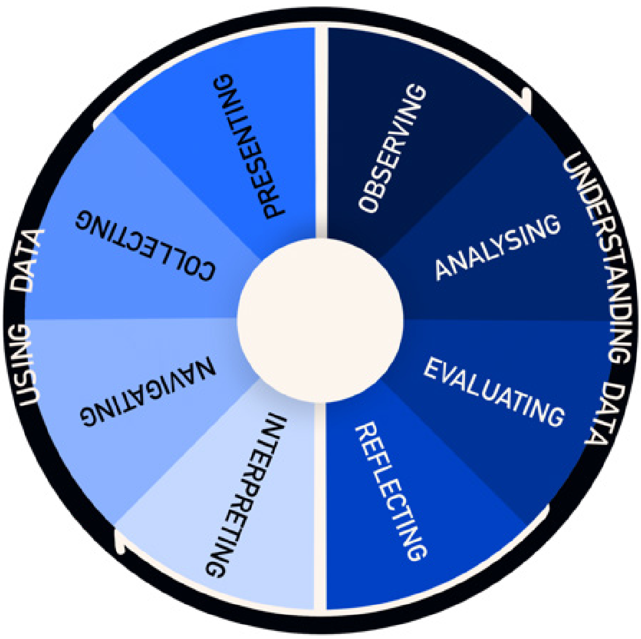

Figure 1. *Data Literacy Competence Model (DLCM)*

The cluster of competences for *using data* is more practical than *understanding data*. However, it breaks with the view, promoted by many data literacy researchers, that data literacy begins by identifying a problem to which data analysis is the answer. The model of the Knowledge Centre follows the levels of literacy in relation to data. The model starts with the questions: Can I read data? Can I navigate types of data? Can I organize data to analytically understand them? Can I collect and work on existing and new data? Can I present and communicate those data? Therefore, the sub-competences are 1) interpreting, 2) navigating, 3) collecting, and 4) presenting. In this model, collecting and actively working with data is not presented as the most valuable or pressing competence. The cluster of competences for *understanding data* is more oriented toward the critical and conscious understanding of data's role in society and individual lives. It is subdivided into 1) observing, 2) analyzing, 3) evaluating, and 4) reflecting.

Conclusion

Smart Cities exemplify the data-rich environments that people live in over time. In these types of environments, technology and the analysis of large data collected provides more intelligent choices and actions—largely automated using algorithms and artificial intelligence—related to mobility, security, energy use, culture, markets, etc. (Ballon et al., 2017). Many of these processes are highly complex and invisible. Yet, some studies on data literacy—and on smart cities—assume that these data will be readily accessible to citizens who will be able to *use the data* actively. We have argued that this may not be the case: not all data gathered at the city level are open source or collected by government. In other words, smart cities are not automatically media and information literate cities. Even if access to data would be warranted, its complex nature makes working with them exclusive to some people. This is the reason why the DLCM begins with *interpreting data* as the basic competence in *using data*.

Thus, it is important for citizens to also *understand* what is going on in their city, how algorithms steer their behavior, and how automated decision-making systems limit—or extend—their choices. Citizens can be navigated through the city or recommended to visit cultural events. Understanding how these systems operate and being able to question their outcomes makes citizens more resilient against biased processes. In the end, *understanding data* should help citizens to keep city planners and local politicians accountable for how these technologies influence their cities. This also implies that cities should be as open and transparent as possible on what technology is used, for what, and how? What data are collected in what form? In addition, cities should work toward open data systems that are easily accessible and allow citizens—and civil society—access and use. Only by developing an active open data context, involving citizens in data projects, empowering civil society participation, and stimulating data literacy in a broad sense will smart cities become media and information literate cities.

We have presented the DLCM, which balances the competences of *using data* and *understanding data*. We have argued that this competence model does not place *collecting* and *actively working with data* at its core but starts with the basic competences of being able to *read* or *interpret data*. We believe this to be a more realistic approach to enhance *data literacy*. As with all competence models, this model is ideal and typical; it concedes that not all citizens will achieve high levels of competences for all sub-competences. Perhaps *actively working with data* might be a more difficult competence in the model. It is also impracticable to shift an entire population to high levels of literacy on all the sub-competences. The goal, however, should be to augment the general level of data literacy throughout society through educational initiatives.

As media literacy is introduced at all levels of education, data literacy should become part of primary, secondary (see Wolff et al., 2017), and tertiary education (see Carlson & Stowell Bracke, 2015; Csernoch & Biró, 2015; MacMillan, 2015; Prado & Marzal, 2013) Initiatives should also focus on improving the *data literacy* of intermediary organizations, civil society, and city personnel. Our experience with smart cities suggests that even within these organizations, expertise to engage with data is lacking. An active city policy around citizens science initiatives—actively involving citizens in data gathering and analysis—might be an excellent way of stimulating engagements in *data literacy*. Data literacy needs an interdisciplinary approach given that data are ubiquitous, and the competences necessary for *using data* and *understanding data* are diverse. The media and information literacy community, which already is highly interdisciplinary in nature (Hobbs, 2005), is well placed to lead data literacy advancements.

References

Ballon, P., van der Graaf, S., & Walravens, N. (2017). De smart city als humane publieke ruimte. In P. Ballon, C. Macharis, & M. Ryckewaert, *De humane stad* (pp. 120–139). Politeia.

Bhargava, R., Deahl, E., Letouzé, E., Noonan, A., Sangokoya, D., & Shoup, N. (2015). *Beyond Data Literacy: Reinventing Community Engagement and Empowerment in the Age of Data*. Data-Pop Alliance & Internews.

Boychuk, M., Cousins, M., Lloyd, A., & MacKeigan, C. (2016). Do We need Data Literacy? Public Perceptions Regarding Canada's Open Data Initiative. *Dalhousie Journal of Interdisciplinary Management*, *12*(1). https://doi.org/10.5931/djim.v12i1.6449

Campkin, B., & Ross, R. (Eds.). (2013). *Future & Smart Cities—Urban Pasmphleteer (Vol. 1)*. UCL Urban Laboratory.

Camponeschi, C. (2011). *The enabling city: Place-based creative problem-solving and the power of everyday*. Enabling City. http://enablingcity.com/

Carlson, J., & Stowell Bracke, M. (2015). Planting the Seeds for Data Literacy: Lessons Learned from a Student-Centered Education Program. *International Journal of Digital Curation*, *10*(1), 95–110. https://doi.org/10.2218/ijdc.v10i1.348

Csernoch, M., & Biró, P. (2015). The Power in Digital Literacy and Algorithmic Skill. *Procedia-Social and Behavioral Sciences*, *174*, 550–559.

De la Peña, B. (2013). The Autocatalytic City. In TED Books (Ed.), *City 2.0: The Habitat of the Future and How to Get There*. TED Books.

D'Ignazio, C., & Bhargava, R. (2015). Approaches to building big data literacy. *Proceedings of the Bloomberg Data for Good Exchange Conference*.

Frank, M., & Walker, J. (2016). Some Key Challenges for Data Literacy. *The Journal of Community Informatics*, *12*(3), 232—235.

Gray, J., Gerlitz, C., & Bounegru, L. (2018). Data Infrastructure Literacy. *Big Data & Society*, *5*(2), 2053951718786316. https://doi.org/10.1177/2053951718786316

Hall, R. E. (2008, September). The vision of a smart city. *Proceedings of the 2nd International Life Extension Technology Workshop,*. International Life Extension Technology Workshop, Paris.

Hobbs, R. (2005). The State of Media Literacy Education. *Journal of Communication*, *55*, 865–871. https://doi.org/10.1111/j.1460-2466.2005.tb03027.x/abstract

Höchtl, J., Parycek, P., & Schöllhammer, R. (2016). Big Fata in the Policy Cycle: Policy Decision Making in the Digital Era. *Journal of Organizational Computing and Electronic Commerce*, *26*(1–2), 147–169.

Hollands, A. (2008). Will the Real Smart City Please Stand Up? *City*, *12*(3), 303–320.

Kithchin, R., & Dodge, M. (2011). *Code/space: Software and everyday life*. MIT Press.

Lee, M. J., Almirall, E., & Wareham, J. D. (2014). Open Data & Civic Apps: 1st Generation Failures–2nd Generation Improvements. *ESADE Business School Research Paper*, *265*.

Leydesdorff, L., & Deakin, M. (2011). The Triple-Helix Model of Smart Cities: A Neo- Evolutionary Perspective. *Journal of Urban Technology*, *18*(2), 53–63.

MacMillan, D. (2015). Developing Data Literacy Competencies to enhance Faculty Collaborations. *Liber Quarterly*, *24*(3), 140–160.

Mediawijs. (2020a). *Data Wisdom? Data Literacy? What does it encompass*. Mediawijs. https://en.mediawijs.be/node/6382

Mediawijs. (2020b). *Dossier: Het Mediawijs Competentiemodel*. Mediawijs. https://mediawijs.be/dossiers/dossier-mediawijs-competentiemodel/dossier-mediawijs-competentiemodel-waaraan-werk-je

Mojsilovic, A. (2018). The age of data and opportunities. *IBM Big Data & Analytics Hub*. https://www.ibmbigdatahub.com/blog/age-data-and-opportunities

Oceans of Data Institute. (2016). *Building Global Interest in Data Literacy. A Dialogue. Workshop Report*. Education Development Center. http://oceansofdata.org/our-work/building-global-interest-data-literacy-dialogue-workshop-report

Oldridge, M. (2017, January 17). Algorithmic Literacy. *Matthew Oldridge*. https://medium.com/@MatthewOldridge/algorithmic-literacy-1d9b5f087142

Open Knowledge Foundation. (2015). *Open Definition*. http://opendefinition.org

O'Reilly, T. (2011). Government as a Platform. *Innovations: Technology, Governance, Globalization*, *6*(1), 13–40.

Peled, A. (2011). When Transparency and Collaboration Collide: The USA Open Data Program. *Journal of the American Society for Information Science and Technology*, *62*(11), 2085-2094.

Prado, J. C., & Marzal, M. Á. (2013). Incorporating Data Literacy into Information Literacy Programs: Core Competencies and Contents. *Libri*, *63*(2), 123–134.

Schaffers, H., Komninos, N., Pallot, M., Trousse, B., Nilsson, M., & Oliveira, A. (2011). Smart Cities and the Future Internet: Towards Cooperation Frameworks for Open Innovation. *The Future Internet Assembly*, 431–446.

Shepard, M., & Simeti, A. (2013). What's So Smart About the Smart Citizen? In D. Hemment & A. Townsend (Eds.), *Smart Citizens (Vol. 4).* Future Everything Publications.

Townsend, A. M. (2013). *Smart cities: Big data, civic hackers, and the quest for a new utopia*. WW Norton & Company.

Van Audenhove, L., Vanwynsberghe, H., & Mariën, I. (2018). Media Literacy Policy in Flanders–Belgium: From Parliamentary Discussions to Public Policy. *Journal of Media Literacy Education*, *10*(1), 59–81.

Vee, A. (2017). *Coding Literacy: How Computer Programming is Changing Writing*. MIT Press.

Wolff, A., Gooch, D., Cavero Montaner, J. J., Rashid, U., & Kortuem, G. (2017). Creating an Understanding of Data Literacy for a Data-driven Society. *Journal of Community Informatics*, *12*(3), 9–26.